EVALUATION AND PERFORMANCE OF DIFFERENT IRRIGATION SCHEDULING METHODS AND THEIR IMPACT ON CORN PRODUCTION AND NITRATE LEACHING IN CENTRAL MINNESOTA

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Chapter 1

Literature review

1.1 Introduction

Nitrogen (N) is a critical nutrient for food grain production such as wheat and maize (Halitligil et al., 2000), hence, the demand for N fertilizer has increased in the United States with increased demand for food production (Economic Research Service, 2019). Also, agriculture is the major contributor of nonpoint source nitrate (NO_3) pollution to surface and groundwater sources, which has many negative environmental impacts such as eutrophication in water bodies and contamination of drinking water sources (Centers for Disease Control and Prevention, 2015; Goolsby et al., 2001; Mitsch et al., 2001). The total cost of potential environmental and health damage through anthropogenic N across the United States has been estimated around $210 billion per year for the early 2000s (Sobota et al., 2015).

Increasing demand for food with growing population and negative environmental and human health impacts of nutrient pollution from agriculture, pose dual responsibility on agriculture. In particular, lack of appropriate management practices in application of agricultural inputs, particularly water and nitrogen fertilizer, negatively impact the environment (J. L. Gabriel et al., 2012; Quemada et al., 2013; Sheikhzeinoddin & Esmaeili, 2017). Therefore, adoption of farm management practices that can reduce nutrient contamination of ground and surface water resources, specifically NO_3-N, and increase food production has become essential. Various farm management practices and their interactions have been found successful to reduce NO3-N leaching to improve ground water quality by researchers around the world(Bohman et al., 2020; Everett et al., 2019; Quemada et al., 2013; Sigua et al., 2016). In this literature review, NO3-N leaching response to farm management practices (use of cover crops, improved fertilizer management, improved irrigation management, etc.) would be discussed.

1.2 Farm management practices to reduce nitrate-N leaching

1.2.1 Use of cover crops to reduce nitrate leaching

The magnitude of N loss through nitrate leaching is significant (Bundy & Andraski, 2005; Harter et al., 2012; Theocharopoulos et al., 1993) and is proportional to NO_3-N concentration of soil solution and volume of subsurface drainage water(Jia et al., 2014). Nitrate losses can occur during the growing season when crop is present and also during the fallow period. Crops such as corn grow only for about six months and after crop maturity more nutrients and water are prone to losses. Some studies have observed most NO_3-N leaching to occur during the fallow period when no plants are growing to use nutrients and water (Shelton et al., 2018; Teixeira et al., 2016). Cover crops are well recognized by the scientific community in terms of their potential for reducing nitrate leaching (Blanco-Canqui, 2018; José Luis Gabriel et al., 2013; Quemada et al., 2013; Thapa et al., 2018). Since cover crops take up and restore remaining nitrogen after cash crop harvest. Additionally, prior research demonstrates that cover crops have no significant impact on cash crop yield (Marcillo & Miguez, 2017). In fact, it is possible to increase cash crop yields and reduce nitrate leaching with cover crops (José Luis Gabriel et al., 2013).

Thapa et al. (2018) observed that non-legume cover crops reduced as high as 56% of nitrate leaching as compared to no cover crop systems. Further, mixtures of legume-nonlegume cover crops reduced significantly more nitrate leaching (Thapa et al., 2018). Cover crop effectiveness on reducing nitrate loss through leaching is dependent upon various other factors, one of them being planting time. Studies show that early fall planting has significantly reduced nitrate leaching while delayed planting did not as compared with no cover (Blanco-Canqui, 2018; Thapa et al., 2018). Cover crop nitrate loss reduction is dependent on many other factors such as cover crop species, climate (precipitation) and cover crop biomass production. It has been observed that high non-leguminous shoot biomass reduces nitrate leaching (Thapa et al., 2018).

Meisinger et al. (2017) studied winter cereal cover crops using soil-column lysimeters for their potential to reduce nitrate leaching in Beltsville, Maryland, US. Interestingly, winter cover crops were able to reduce up to 95% of nitrate leaching as compared to no cover in dry seasons (Meisinger & Ricigliano, 2017). The findings of this study are supported by another study conducted by Everett et al. at 19 sites (15 on-farm and 4 research station) in southern and central Minnesota, where winter rye cover crop was found to significantly improve N uptake, reducing N leaching (Everett et al., 2019). Another study by Kladivko et al. (2014), studied the potential of cover crop adoption to improve water quality in five upper Midwestern states (Ohio, Indiana, Illinois, Iowa, and Minnesota) (Kladivko et al., 2014). The simulations from Root Zone Water Quality Model used in the study, suggested that cover crop adoption in the region not only has the potential to reduce nitrate loss but would also reduce the total nitrate load to the Gulf of Mexico.

1.2.2 Improved N fertilizer management to reduce nitrate leaching

Although increase in fertilizer application rates has been observed to increase corn yield (Sexton et al., 1998), a large portion of the applied N fertilizer is not taken up by the crop and contributes to NO_3-N leaching to ground and surface water sources(Asadi et al., 2002; Cai et al., 2002; Jia et al., 2014). Scientists believe that leaching of nitrates below crop root zone can be reduced by managing nutrient and water input to the crop (Chen et al., 2017; Gheysari et al., 2009; Jia et al., 2014). Asadi et al. conducted a field experiment involving four N rate treatments – 0, 100, 150 and 200 Kg N/ ha. In this 2-year experiment, the treatment with the highest nitrogen rate (N200) resulted in higher nitrate leaching in both years (Asadi et al., 2002). The total seasonal fertilizer application in this study was done in three parts 30%, 30% and 40% of total fertilizer applied at 7, 24 and 45 days after planting respectively via a solid set sprinkler system. Although grain yield generally increased with increase in fertilizer rates but in one of the years the treatment with nitrogen rate 150 Kg N/ ha had higher yields than 200 Kg N/ ha treatment. However, the N loss increased consistently with increase in fertilizer rates in both the years(Asadi et al., 2002). This calls for the importance of optimization of N fertilizer since greater N rates might not always produce high yields but have shown greater potential to cause contamination of ground and surface water sources through nitrate leaching.

Variation in soil types and properties both spatially and temporally leads to variation in nutrient concentrations in soils across croplands which leads to the idea of site-specific N management. Site specific nitrogen management is successfully practiced across various studies (Delgado et al., 2005; Ferguson et al., 2002; Muschietti-Piana et al., 2018). Muschietti-Piana et al. conducted a site-specific N management study in high and low productivity zones in soils of the Inland Pampas region of Argentina. The goal was to identify and manage homogenous areas within a field under site specific management (SSM) and compare them with the otherwise uniform management (UM). ArcGIS was used for management zone delineation with high productive (HP) zones having 20% higher grain yield and low productive (LP) zones having 30% lower grain yield than field average yield across multiple years (Muschietti-Piana et al., 2018). Surface broadcast urea (46-0-0) via variable rate fertilizer controller was applied in the fields. When site specific management results were compared with that of uniform management it was found that corn yield increased by 2.7 Mg/ ha and 18% reduction in potentially leachable residual nitrogen was obtained (Muschietti-Piana et al., 2018). While calculating nitrate loss, it is important to consider accumulated nitrogen along with leached nitrogen as accumulated nitrogen has a potential to leach when the wet season arrives (Azad et al., 2018).

In N fertilizer management studies, the extraction of soil solution for determining nitrate levels can be done by ceramic suction cup samplers or lysimeters (Chen et al., 2017; Gheysari et al., 2009; Sigua et al., 2016; Zheng et al., 2020). Lysimeters have been used for various purposes but weighing lysimeters are thought of as the standard technique for determining evapotranspiration and quantity and quality of water loss through seepage (Chávez et al., 2009; Klammler & Fank, 2014). Zheng et al. conducted an extensive lysimeter study which involves fifteen auto-weighing lysimeters to quantify nitrate leaching in a three-year field experiment. The study consisted of four N fertilizer treatments with 2 N fertilizer types (monotypic uncoated urea vs. blend product of controlled-release urea (CRU) and uncoated urea) and 2 N rates (150 & 225 Kg N/ hm^2) along with a no-N control in which no external N fertilizers were used(Zheng et al., 2020). Flood irrigation was applied, and amount and timing of irrigation were strictly kept uniform across all treatments such that all other factors were kept constant apart from N treatment. Weighing lysimeters were used to monitor evapotranspiration (ET) and leachate throughout the study. The results of this study suggest that the blended product of controlled-release and uncoated urea produced significantly lower nitrate leaching as compared to uncoated urea on the same application rate as the blended product provided slow release of nitrogen as per crop N demand. The results of this study are consistent with other studies in the field which suggests that to reduce nitrate leaching in percolating water, N fertilizer should be split applied in amounts and timing optimum to crop N demand(Jia et al., 2014; Struffert et al., 2016). Since the amount of nitrate leaching is proportional to both nitrogen concentration and volume of soil water, it is important to study the water balance along with N balance in order to develop strategies for reduction of nitrate loss from agriculture.

1.2.3 Fertilizer management combined with irrigation management

Both irrigation and fertilizer management practices have been individually successful in reduction of nitrate loss from agriculture (Muschietti-Piana et al., 2018; Wang et al., 2014; Zheng et al., 2020). Interaction of irrigation and fertilizer management treatments involving synchronization of irrigation and fertilizer application amounts and timings in accordance with crop demand, can potentially reduce nitrate leaching (Azad et al., 2020). Azad et al. used the HYDRUS-2D model to simulate water flow and N transport in one such combination of irrigation and fertilizer treatment in a surface micro-irrigation system. In this study, two fertigation (fertilizer applied through irrigation) schedules were compared as treatments. The first fertigation schedule involved split application of 50%, 25% and 25% of the total N fertilizer in accordance with the regional scheduling recommendations. While the second schedule involved regular weekly application of the same amount of total N fertilizer evenly distributed over the growing season. Flow rate of irrigation in this study was selected based on soil type.

As opposed to a previous study (Asadi et al., 2002), in which fertilizer was applied at the beginning of irrigation event, (Azad et al., 2018) always applied fertilizer at the end of irrigation event in order to prevent downward flow of nutrients along with water due to immediate irrigation (Azad et al., 2018). The results of the study indicated that the total nitrate loss (leached and accumulated nitrate) which was 43.83% with the traditional fertigation schedule, reduced to 23.41% without significantly impacting corn yield (Azad et al., 2018). This can be attributed to the fact that the excess accumulated nitrate (beyond crop requirement) in the traditional fertigation schedule leached in the subsequent irrigation or precipitation events. The results of this study are in accordance with another study (Zheng et al., 2020) which showed that slow release of N fertilizer over the crop growing period reduced nitrate leaching.

Irrigation can be calculated through soil moisture deficit (SMD) which is the amount of water depleted from soil water storage available for crop uptake. An experiment involving four irrigation amounts (0.7, 0.85, 1.0 and 1.13 SMD) and three nitrogen levels (0, 142 and 189 Kg N/ ha) was conducted by Gheysari et al. in 2009 which involved the use of ceramic suction cups for soil solution sampling as other related studies (Chen et al., 2017; Gheysari et al., 2009; Jia et al., 2014). They found that total seasonal nitrate leaching was affected (reduced) more significantly by interaction of irrigation and nitrogen treatments ($p<0.0001$) than individual irrigation treatments ($p<0.0026$). Apparently, there exists a contradiction in the study conducted by Liang et al. where irrigation treatments had a more prominent effect on nitrate leaching, but that was an exceptional study where irrigation water had high nitrate concentrations and 45-48% of total nitrogen input to the field came from irrigation water (Liang et al., 2016). Another combined irrigation and nitrogen management study (Jia et al., 2014) has confirmed the results shown by Gheysari et al., where the interaction of irrigation and nitrogen treatments were able to reduce nitrate leaching at a similar significance ($p<0.0001$).

A study conducted by Chen et al. (2017) compares traditional irrigation and nitrogen treatments with the ones based on monitoring of soil properties. The study proclaims that interaction of irrigation and fertilizer treatments has the potential to reduce nitrate loss beyond what is possible through fertilizer management alone, up to 85.2% of nitrate leaching can be avoided using irrigation and fertilizer management treatments based upon continuous monitoring of soil moisture properties (Chen et al., 2017). Also, the traditional irrigation treatment in this study was able to produce farmland water leakage even during a drought year. A prior study by Asadi et al. (2002) suggested that nitrate loss through fertigation was lower than otherwise even at a higher N application rate (Asadi et al., 2002).

1.2.4 Irrigation management strategies for nitrate loss reduction

Prior research confirms a positive relationship between N and water use efficiency (Muschietti-Piana et al., 2018; Quemada Miguel, 2016). Therefore, monitoring water balance and optimizing water resources in order to increase N use efficiency is important especially in soils with low water holding capacities (Sigua et al., 2016). Irrigation and precipitation are the two water inputs that contribute to deep percolation, out of which irrigation can be managed and optimized. Prior research suggests that the reduction in irrigation efficiency is mainly due to percolation (Bouwer, 1994). Further, a recent study by Bohman et al. showed that, reducing the rate of irrigation by 15% resulted in the decrease of NO3-N leaching by 17% through reduction in deep percolation of water below the rootzone of the crop (Bohman et al., 2020).

HYDRUS-2D is one of the many models successfully used to study water and N balance (Hanson et al., 2006) and Wang et al. used the HYDRUS-2D to model a drip irrigation system which is widely accepted as a method to improve water and N use efficiency where drip system uniformity is one of the main factors that impact deep percolation and nitrate leaching (Barragan et al., 2010). Wang et al. simulated three levels of coefficients of uniformity (CU) over 32 years of precipitation patterns and found that higher level of uniformity potentially leads to a more uniform distribution of water and nutrients in soil, resulting in less nitrate leaching(Wang et al., 2014).

Inputs to the water balance (precipitation and irrigation) strongly impact the amount and timing of nitrate leaching as deep percolation is observed immediately after a rain or irrigation event (Wang et al., 2014). As uniformity of the drip system (CU) increased from 60% to 95%, the mean NO_3-N leaching rate reduced by 36% in the dry (low precipitation) season (Wang et al., 2014). On the other hand, when wet (high precipitation) seasons were observed, an increase of drip system uniformity from 60% to 95% resulted in a reduction of only 4% nitrate leaching as precipitation (and not irrigation) was the dominant factor to induce nitrate leaching.

Also, precipitation is considered one of the main factors that influence water and N balance in agricultural systems and hence nitrate leaching (Asadi et al., 2002; Meisinger & Ricigliano, 2017; Wang et al., 2014). Meisinger et al. suggested that N leaching was more affected by quantity of precipitation during cover crop establishment season than by cover crop species (Meisinger & Ricigliano, 2017).

Asadi et al. found that nitrate leaching was strongly connected to precipitation periods. In one of the years of the study 91% of the total nitrate leaching occurred during rainfall events (Asadi et al., 2002). Wang et al. found that precipitation was the governing factor in determining nitrate leaching as most nitrate leaching happened in the period from June-September where 70-80% of total precipitation happened in this period in the North China Plain (Wang et al., 2014). Similar results were obtained by Struffert et. al (2016) in a study conducted in Central Minnesota (Struffert et al., 2016).

A study conducted by Pang et al. at Staples, Minnesota using CERES Maize Model simulated that NO_3-N leaching potential was influenced more by irrigation trigger level than by other factors – N application rates and climate (Pang et al., 1998) due to high permeability and low water holding capacity soils present in the region. Therefore, the importance of inclusion of water balance to reduce nitrate leaching becomes more important as water present in low water holding capacity soaks in quickly and has the potential to take nutrients along with it. In agricultural lands, it is therefore important to maintain a soil moisture level between permanent wilting point and field capacity of soil such that the soil has just enough water to support crop requirements.

Sigua et al. conducted a study in which they compared the impact of three irrigation scheduling methods on corn yield and nitrate leaching on low water holding capacity soils. The three scheduling methods were Irrigator PRO (IPRO) (USDA), Normalized Difference Vegetative Index (NDVI) (remote sensing based) and Soil

Water Potential (SWP) based on soil water potential. Although the irrigation scheduling methods recommended different amounts and timing of irrigation the yields were not significantly impacted by the type of irrigation scheduling method used. However, one of the methods – IPRO, was able to reduce 30-40% of nitrate leaching as compared to other methods (Sigua et al., 2016). This again confirms the importance of irrigation scheduling in nitrate loss reduction especially in soils with low water holding capacities. Further Sigua et al. found that the impact of irrigation scheduling on nitrate leaching was more significant than nitrogen fertilizer rates (Sigua et al., 2016). Another study conducted by Liang et al., got similar results. Liang et al. (2016) conducted an experiment by simulating 240 different irrigation and fertilizer treatments consisting irrigation (15) and fertilizer (16) levels in the WHCNS model. They found that the main factor influencing the risk of nitrate leaching was the amount of irrigation. Further, they simulated minimum nitrate leaching with a certain reduced irrigation level (491 mm) without impacting crop yield (Liang et al., 2016). Also, studies have shown that crop N uptake can be improved by altering frequency of fertigation (Farneselli et al., 2015; Silber et al., 2003).

1.3 Conclusions

Anthropogenic release of nitrogen has the potential to cause negative impacts on the environment and human health which results in high social costs. Agricultural activities contribute a large share towards nitrate pollution of ground and surface water. Studies show that appropriate farm management strategies can help mitigate NO3-N pollution and decrease nitrate contamination of water bodies.

Cover crops have the potential to reduce nitrate leaching as they take up available nutrients and water during the fallow period when no cash crops are growing to consume those nutrients. Planting time, biomass production, climate (precipitation) and cover crop species are the primary factors that influence cover crop effectiveness in reducing nitrate leaching. Non-legume cover crops are observed to have reduced nitrate leaching for up to 56% as compared to no cover. High non-leguminous shoot biomass has shown higher potential to reduce nitrate leaching. Adoption of cover crops in the upper Midwest region has been simulated to reduce around 20% of nitrate load going into the Gulf of Mexico from the region.

Loss of nitrate nitrogen with deep percolating water can also be reduced by irrigation and fertilizer management strategies. In general, N fertilizer application rates positively impact both corn grain yield and nitrate leaching. However, beyond a certain N fertilizer application rate corn grain yield cannot be increased by increasing N fertilizer application and may contribute towards excessive nitrate leaching. Therefore, optimization of N fertilizer rates is important since greater N rates have greater potential to cause contamination of ground and surface water through nitrate leaching. Variation in soil types and properties both spatially and temporally leads to variation in nutrient concentrations in soils across croplands. Therefore, site specific nutrient management can be useful in nitrate loss reduction. Regular supply of controlled amounts of fertilizer would lead to an increase in nitrogen use efficiency and crop N uptake and reduce nitrate losses due to leaching of nutrients.

There exists a positive relationship between N and water use efficiency and interaction of irrigation and fertilizer treatments has the potential to reduce nitrate loss beyond what is possible through either one alone. Inputs to the water balance (precipitation and irrigation) strongly impact the amount and timing of nitrate leaching as deep percolation is observed immediately after a rain or irrigation event. Therefore, irrigation scheduling is important for nitrate loss reduction especially in soils with low water holding capacities. Some studies suggest that potential impact of irrigation schedule management on reducing nitrate leaching can be more significant than nitrogen fertilizer management.

Chapter 2

Field evaluation of irrigation scheduling methods in coarse textured soils

2.1 Overview

An increase in corn (*Zea mays* L.) grain production has been witnessed in the United States since the 1960s. Although this increase in corn production has satisfied the needs of a growing world population, management practices for N and water that sufficiently protect the environment are insufficient. Soils with low available water holding capacities (coarse-textured soils) cannot store a lot of water which is available for plant uptake. Hence these soils require meticulous monitoring of soil water levels and controlled supplemental irrigation. Insufficient irrigation may diminish crop yields and leave more N unused through reduced uptake which is susceptible to losses. Excess irrigation has the potential to contaminate ground and surface water sources through deep seepage of nutrients (applied as fertilizers) below the root zone of crop. Many private drinking wells in Central and Southwestern Minnesota have NO_3-N concentrations greater than the USEPA standard for drinking water (10 mg/L).

Prior research suggests that fertilizer and water management strategies can potentially reduce agricultural NO_3-N leaching. Though a significant amount of research has been conducted to study the impact of fertilizer management on nitrate leaching, only a limited research has been conducted to explore the role of irrigation management alone in reducing nitrate leaching. Irrigation scheduling involves estimating actual crop water requirement and maximizing the accuracy and precision in terms of the amount and timing of irrigation applied. This two year study is conducted at two sites in Central Minnesota on four different irrigation scheduling methods involving different principles and strategies (weather-based, soil-moisture based, simulation-based) to compute irrigation requirements. These irrigation scheduling methods are compared in terms of recommended irrigation amounts, crop evapotranspiration, N uptake and the potential to reduce irrigation-induced NO_3-N leaching in coarse-textured soils without significantly impacting crop yield.

One of the irrigation scheduling methods, Irrigation Management Assistant (IMA) Tool resulted in significantly lower total water application and still obtained similar yields as compared to other scheduling methods. The study demonstrates that adoption of appropriate irrigation scheduling methods in coarse-textured soils can reduce agricultural water loss by up to 65% which directly contributes to significant reduction in costs pertaining to procurement and application of irrigation water. It was observed that both corn grain yield and crop N uptake were not significantly ($p<0.05$) impacted by the irrigation scheduling method used. Significant differences in nitrate leaching between different irrigation scheduling treatments were observed. Therefore, irrigation scheduling has the potential to significantly reduce the amount of water and N loss without impacting corn grain production in coarse textured soils. Also, 83 % reduction in nitrate leaching was observed with 37% decrease in precipitation amounts at one of the sites.

2.2 Introduction

Advances in technology and improvement in production practices in the past decades have led to an increase in agricultural production in the United States. The total harvested cropland in the United States has increased by 2 million hectares from 2012 to 2017 (USDA NASS, 2012). With increasing agricultural production, plant consumption of N in the US increased by 8.68% in four years from 2010 to 2014, also in 2014, 47.5% of the total plant nitrogen use in the U.S., was by corn crop (Economic Research Service, 2019).

Irrigation is applied to more than two-hundred thousand farms in the U.S. and the total farm area irrigated is greater than 22 million hectares (USDA NASS, 2013). The amount of irrigation in terms of quantity of water applied is greater than 109 billion cubic meters (USDA NASS, 2013). It has been confirmed by prior studies that water stress is critical to corn yield and appropriate timing and amount of irrigation has demonstrated an increase in corn yield (El-Hendawy & Schmidhalter, 2010; Stone et al., 2010). Unfortunately, increase in agricultural production and lack of appropriate management practices in application of agricultural inputs, particularly water and fertilizer, negatively impact the environment (Sheikhzeinoddin & Esmaeili, 2017).

The Western States (17 conterminous west states of the United States) constitute a great proportion (81 percent) of the total irrigation water withdrawn in the U.S. (USGS, 2021). Surface water has been reported as the primary source of irrigation water for most of the states in the arid west region (USDA NASS, 2018). Although for some states in the west including Nebraska, Texas, Kansas and Oklahoma more groundwater was withdrawn for irrigation application than surface water (USDA NASS, 2018). Apart from the arid west states, many other states including Minnesota, Wisconsin, Illinois, Missouri, Arkansas, Louisiana also require irrigation in the United States (USDA NASS, 2013). In Minnesota, although irrigation requirements are generally lower in comparison to arid west states, irrigation management is difficult due to uncertainty in precipitation and hence nitrate leaching. In Minnesota 866 thousand hectares of land was irrigated and most of the irrigation water is pumped from groundwater wells (USDA, 2013; USDA NASS, 2017). The total land in irrigated farms in Minnesota has increased by 12.6% from 2012 to 2017 (USDA NASS, 2017).

The Central sands region in Minnesota has coarse textured soils and low available water holding capacities and therefore requires irrigation for obtaining ideal yields for corn. In irrigated sandy soils, nitrogen has the potential to leach below the root zone as nitrate nitrogen (NO_3-N) (Struffert et al., 2016), which may cause nitrate pollution in ground water. Many private drinking wells in Central and Southwestern Minnesota have NO_3-N concentrations greater than the USEPA standard for drinking water (10 mg/L) (Minnesota Department of Health, 2021). Twenty-one percent of the total population of Minnesota, which amounts to almost 1.2 million people, uses private wells for drinking water. Government agencies spend substantial amounts of funds to ensure safe drinking water for private well user households. Households that rely on private well water for drinking water can apply for up to $100,000 of funding under the Clean Water Fund by Minnesota Department of Health for testing or treatment of nitrate in drinking water (*Private Well Protection, Clean Water Fund*, 2021).

Through adoption of appropriate farm management practices, particularly irrigation management, reduction in the negative impact of agriculture on groundwater quality and quantity can be achieved. Better irrigation scheduling is the key to address the problem of nutrient leaching in Central Minnesota. Fundamentally, irrigation scheduling is the process of determining crop water requirement and maximizing the accuracy and precision in terms of the amount and timing of irrigation to be applied. Over-irrigation wastes water and has the potential to cause nutrient leaching and hence contaminating ground and surface water sources. On the other hand, insufficient irrigation can hamper crop growth, reduce quality and quantity of yield and is a potential threat to food security. This makes irrigation scheduling critical, especially for a region having coarse textured soils with low water holding capacities.

This study is focused on the role of irrigation scheduling methods in generating agronomic and environmental responses associated with corn production for coarse textured soils in Central Minnesota region. Irrigation scheduling has various approaches, dependent upon the knowledge, skill and equipment used for irrigation scheduling. Irrigation may be triggered simply based on visual appearance of crop or appearance and feel of soil. Also, there are weather based irrigation scheduling methods that calculate soil water requirements through computing weather parameters. Other approaches include soil moisture monitoring using soil moisture sensors and the application of mathematical simulation models to simulate irrigation requirements. In this study various irrigation scheduling methods are compared in terms of irrigation amounts, N uptake, seasonal crop evapotranspiration, corn grain production and nitrate leaching. The goal of this study is to evaluate irrigation scheduling methods in order to optimize irrigation scheduling to minimize groundwater nutrient pollution and improve groundwater quality and quantity without significantly impacting corn production.

The objective of this study is to evaluate the impact of four irrigation scheduling methods on nitrate leaching and corn grain yield.

2.3 Materials and Methods

2.3.1 Site description

Field trials were conducted for two consecutive corn growing seasons 2019 and 2020 (Y1, Y2) at two research sites. One at the Sand Plain Research Farm (SPRF) in Becker, Minnesota (45°23'N 93°53'W) (S1) and the other at the Rosholt Research Farm in Westport, Minnesota (45°42'N 95°10'W) (S2). Both sites are in Central Minnesota and have coarse textured soils with low available water storage and need irrigation to prevent crop water stress.

The soil at S1 is Hubbard-Morford complex (sandy, mixed, frigid, Entic Hapludoll) which is a glacial outwash soil and has a sandy alluvium parent material with 0-3 % slopes. In the top 120 cm of soil, this soil has bulk density of 1.66 g/cm^3, organic matter content of 0.79 %, field capacity volumetric water content of 12.0% and permanent wilting point of 4.2 % (Web Soil Survey NRCS USDA, 2021). The soil at S2 is Arvilla sandy loam (sandy, mixed, frigid, Calcic Hapludoll) with loamy glaciofluvial deposits over sandy and gravelly outwash parent material with 0-2% slopes. In the top 120 cm of soil, this soil has bulk density of 1.61 g/cm^3, organic matter content of 0.72 %, field capacity volumetric water content of 12.7 % and permanent wilting point of 5.8 % (Web Soil Survey NRCS USDA, 2021). Although these soils have higher organic matter content at shallow depths – 2.03% and 1.23 % at 0-30 cm and 0-60 cm respectively. Table 2.1 and 2.2 show the soil texture classification percentage and available water storage for both the sites. Both sites had high sand percentage, and hence low available water. The first 120 cm of soil have less than 10 cm of available water.

The plots were in a continuous corn cropping system at both locations. Chisel plow was used to till the soil to a depth of 15-20 cm at S1. For S2, Orthman strip till equipment was used as strip till combines the benefits of chisel plowing and no-till for row crops. The individual plot size was 12.19 m x 18.29 m at S1and 7.62 m x 15.24 m at S2. The number of rows planted with corn crop in each plot were 16 and 10 for S1 and S2 plots respectively. Total growing season precipitation in Y1 was 632 mm and 538 mm for S1 and S2 respectively. For growing season Y1 total seasonal precipitation was 402 mm and 457 mm for S1 and S2 respectively.

Table 2.1. Particle distribution in the top 120 cm of soil at sites S1 and S2

Particle	S1	S2
Sand (%)	87.9	80
Silt (%)	8	12.3
Clay (%)	4.1	7.7

(Web Soil Survey, NRCS, USDA)

Table 2.2. Available water storage in the top 120 cm of soil at sites S1 and S2

Soil Depth (cm)	AWS (cm) S1	AWS (cm) S2
0-30	3.4	4
30-60	2.67	2.78
60-90	2.04	0.99
90-120	1.59	0.96
0-120	9.71	8.74

(Web Soil Survey, NRCS, USDA)

2.3.2 Irrigation treatments

The study consists of a randomized complete block design with four irrigation scheduling methods replicated 3 times. The four irrigation scheduling methods are the checkbook method (CB) (weather based), online irrigation management assistant tool (IMA) (weather based), soil moisture monitoring using soil moisture sensors (SM) (soil moisture based) and crop growth model (The EPIC crop growth model) (simulation model).

The checkbook method for irrigation scheduling is a weather-based irrigation scheduling method which is fundamentally based on the water balance approach. The change in soil water storage in the root zone of the crop is determined by calculating the difference between total water inflow and total water outflow in the system. The water inflow to the system constitutes precipitation and irrigation amounts and the outflow from the system is crop evapotranspiration and water losses mainly due to runoff and drainage or deep percolation beyond the root zone of the crop.

Broadly, the method operates like a ‘checkbook’ where estimated crop water use for each day is added to the previous day’s soil water deficit and any water inflow due to rainfall or irrigation is subtracted. The soil water deficit or net irrigation requirement is calculated using the following equation.

$$D_c = D_p + ET_c - P - I \qquad (1)$$

Where D_c stands for soil water deficit (net irrigation requirement) in the rooting zone on current day, D_p is the previous day soil moisture deficit, ET_c is the crop evapotranspiration on the current day, P is the precipitation for the current day, and I is the irrigation amount for the current day.

$$ET_c = ET_{ref} \times K_c \tag{2}$$

Daily crop evapotranspiration (ET_c) values are estimated from daily reference evapotranspiration values (ET_{ref}) derived from Jensen-Haise equation which involves the incorporation of two weather parameters – solar radiation and temperature and crop coefficient curves (K_c) developed for corn for North Dakota (Stegman et al., 1977).

Jensen-Haise equation used in the CB method requires fewer weather parameters (temperature, solar radiation) as compared to other equations used for determination of reference evapotranspiration (ET_{ref}).

Stegman et al. used the following ET_{ref} calculation incorporated from the Jensen-Haise equation (Stegman et al., 1977).

$$ET_{ref} = (0.014T_a – 0.37)\ R_S \tag{3}$$

$Ta = (T_{max} + T_{min}) / 2$

Ta = Mean daily air temperatures (°F)

T_{max} and T_{min} = maximum and minimum daily air temperatures (°F)

R_s = solar radiation in inches of water equivalent; heat of vaporization was taken as 585 calories per gram

In this study a spreadsheet model of the Checkbook method is used, which requires values of daily maximum temperature and daily effective rainfall along with week past emergence of crop to determine Soil Water Deficit (SWD) (Steele et al., 2010; Wright, 2002). Data requirements for effectively using the CB spreadsheet include historical or forecasted maximum daily temperature, AWHC value, crop type, emergence date, rainfall and irrigation data. Also, periodic field visits to monitor crop development and soil water content are recommended (Steele et al., 2010). If a particular growing season produces accelerated or delayed crop development a fictious planting date slightly ahead or before the original planting date can be entered in the spreadsheet as an adjustment to account for the change observed in the field (Steele et al., 2010). Management Allowable Depletion (MAD) is the maximum soil water depletion that an irrigation manager allows beyond which irrigation is triggered. MAD was dependent upon crop type and growth stage, and a value ranging from 40-60% of available water holding capacity (AWHC) of soil was chosen in this study.

Irrigation Management Assistant Tool (IMA) is an online platform that automates aspects of daily soil moisture calculations based on a field's soil and current conditions including weather, crop and crop growth stage. This tool was developed in 2016 through a three-year LCCMR project paid by a grant from Minnesota Environmental and Natural Resources Trust fund for the Little Rock Creek Groundwater area and 5-county expanded areas of Hubbard, Becker, Wadena, Otter Tail and Todd counties of Minnesota. In these pilot areas, the tool has been adopted by over 100 regular users to irrigate 5 different crops (corn, soybeans, alfalfa, potatoes, and edible beans) covering roughly 6,500 acres. The success of IMA in these regions and interest shown by other soil water conservation districts in MN and growers throughout MN revealed the need to evaluate the efficacy of this systems in terms of volumes of water applied as compared to other traditional and labor intensive irrigation scheduling tools. For this project the tool was expanded to Pope and Sherburne Counties of MN to accommodate our research sites.

This tool is a weather-based irrigation scheduling tool that uses the water balance approach to estimate soil water deficit (equation 1). Crop evapotranspiration (ETc) is estimated using equation 4

$$ET_c = ET_r \times K_c \times K_a \quad (4)$$

where ET_r is daily alfalfa reference evapotranspiration calculated using Penman-Monteith equation (Monteith 1965; Allen et al., 1998) with a fixed canopy resistance (ASCE-EWRI 2005). Weather variables including solar radiation, rainfall, maximum and minimum air temperatures, wind speed, and humidity are used to compute daily values for ETr. For this study, the tool used weather data from the weather station at the research site (http://agweathernetwork.com/). ASCE-EWRI manual 70 crop coefficient (Kc) values for corn are used to model daily ET_c for irrigation scheduling (Jensen and Allen, 2016). Ka is the resistance of water transfer to the atmosphere for current percentage of field capacity. The tool uses the gridded Soil Survey Geographic Database (gSSURGO) for information on site-specific soil physical properties such as soil texture, soil water holding capacity and field capacity. For rainfall data, the IMA tool uses the National Centers for Environmental Prediction (NCPE) stage IV rainfall data. In our study, for Y1 growing season we used the tool estimated rainfall values, however, in Y2 we realized that rainfall values can also be overridden by the user. The rainfall values were overridden whenever the tool estimated rainfall was more than ±5% of the actual rainfall measured at the site. Irrigation is entered by the user. Other user inputs required at the beginning of the irrigation season include field location, field irrigation delivery rate (gpm), crop type, initial soil moisture, planting date and maturity date. The soil water balance estimated using equation 2 can be overridden by the user but in our study, we did not override the soil water balance values and used the tool estimated values for irrigation scheduling. Similar to MAD value used in the CB method the IMA tool uses a minimum allowable soil moisture (MASM) value which represents irrigation trigger. The MASM value is based upon crop, crop growth stage, planting date and soil properties at the field, the MASM values keep on changing automatically with the progression of the crop and the growing season. The IMA tool monitors field water balance (FWB) throughout the growing season and irrigation is triggered when FWB reaches MASM.

Soil-moisture based irrigation scheduling involves direct calculation of soil water deficit through field measurements of soil water content. In this study neutron moisture meter, InstroTek 503 ELITE Hydroprobe, was used to conduct weekly measurements of volumetric water content of soil. Further, volumetric water content was used to calculate soil water deficit in the root-zone of the crop. Irrigation was triggered whenever the soil water depletion in the root zone was 40%-60% (depending on corn growth stage) of AWHC of soil. As in the case of previous scheduling methods, irrigation amounts were kept in accordance with soil water deficit experienced by soil, to bring back the soil water level close to field capacity while leaving some room for expected precipitation events.

Environmental Policy Integrated Climate (EPIC) Model is a mathematical model that simulates crop growth parameters (Texas A&M, 2021). It is a field scale model that particularly simulates yield, water and N balance. It functions at a daily time step and can function for hundreds of years of continuous simulation. In this model various attributes including weather data – solar radiation, maximum and minimum daily temperature, precipitation, relative humidity, windspeed and soil properties – soil water upper limit, soil water lower limit, soil texture and crop attributes – crop type, planting date and cropping system are taken as inputs. The irrigation application strategy is specified by irrigation codes, [0] for dryland, [1] for sprinkler irrigation, [2] for flood or furrow irrigation, [3] for fertigation, [4] for lagoon and [5] for drip irrigation and irrigation requirements, grain yield, drainage, N uptake and nitrate leaching can be obtained from the model. The model has more than 200 inputs with a wide range of applications. Users can input only those parameters which are critical to simulated output or to which the output is thought to be most sensitive to. In this study, the objective was irrigation scheduling, i.e., amount and timing of irrigation, critical inputs were soil water lower limit, soil water upper limit, solar radiation, maximum and minimum daily temperature, precipitation, relative humidity, windspeed, soil texture, crop type, planting date, irrigation code and cropping system. Field measurements were utilized for calibration and validation of the simulated model. For one of the sites (S2) EPIC model was previously calibrated using 4 years of field data from an adjacent site from another study.

During the study, half of the data was used for calibration of the model and the other half for validation of the calibrated model.

A linear move irrigation system was used for irrigation application at both sites. Table 2.3 and 2.4 show irrigation amounts and date of application for each of the four irrigation scheduling methods. Irrigation was recommended in the months of June, July and August for all irrigation treatments at all four site years of the study. In Y1, a total of 10 irrigation events happened at S1 and 5 irrigation events at S2 for all treatments combined. In Y2, the number of irrigation events increased to 12 and 8 for S1 and S2 respectively. At S1, highest irrigation was recommended by SM method of irrigation scheduling for both Y1 and Y2 growing seasons and IMA method recommended lowest irrigation. At S2, the CB method of irrigation scheduling provided highest irrigation and lowest irrigation was recommended by IMA tool based irrigation scheduling for both Y1 and Y2.

Table 2.3. Irrigation amounts (mm) and application dates as recommended by irrigation methods for Y1 growing season at sites S1 and S2

Y1 Irrigation amounts (mm) and date of application								
Date	S1				S2			
Planting Date	May-06				May-29			
Irrigation Treatment	SM	CB	IMA	EPIC	SM	CB	IMA	EPIC
6-Jun	12.7	12.7	12.7	12.7	0	0	0	0
29-Jun	7.62	7.62	7.62	7.62	0	0	0	0
12-Jul	24.13	17.78	0	8.636	0	0	0	0
23-Jul	24.13	0	0	14.478	0	0	0	0
24-Jul	0	0	0	0	0	0	0	7.62
25-Jul	20.32	25.4	0	15.24	0	25.4	0	10.16
31-Jul	0	20.32	0	0	0	0	0	0
2-Aug	17.78	0	0	11.43	0	0	0	12.7
5-Aug	0	0	0	0	0	21.59	0	7.62

6-Aug	22.86	25.4	0	12.7	0	0	0	0
9-Aug	15.24	19.05	0	10.16	12.7	21.59	0	10.16
12-Aug	0	0	20.32	0	0	0	0	0
Harvest Date	Oct-24				Nov-03			
Total Irrigation	144.78	128.27	40.64	92.964	12.7	68.58	0	48.26

Table 2.4. Irrigation amounts (mm) and application dates as recommended by irrigation methods for Y2 growing season at sites S1 and S2

Y2 Irrigation amounts (mm) and date of application								
Date	S1				S2			
Planting Date	May-13				May-22			
Irrigation Treatment	SM	CB	IMA	EPIC	SM	CB	IMA	EPIC
4-Jun	10.16	10.16	10.16	10.16	0	0	0	0
11-Jun	0	0	0	0	10.16	10.16	10.16	10.16
14-Jun	11.43	0	0	11.43	0	0	0	0
24-Jun	25.4	25.4	0	0	0	0	0	0
30-Jun	8.89	8.89	8.89	8.89	0	0	0	0
7-Jul	25.4	25.4	25.4	25.4	0	0	0	0
14-Jul	25.4	25.4	25.4	25.4	0	0	0	0
17-Jul	0	0	0	0	12.7	17.78	0	17.78
29-Jul	25.4	25.4	0	11.43	0	0	0	0
30-Jul	0	0	0	0	17.78	17.78	0	17.78
3-Aug	21.59	25.4	0	0	0	0	0	0
5-Aug	0	0	0	17.272	17.78	17.78	0	17.78
10-Aug	0	0	17.78	0	0	17.78	17.78	17.78
20-Aug	0	0	0	0	17.78	0	0	0
21-Aug	25.4	0	0	0	0	0	0	0
24-Aug	0	0	0	0	0	17.78	0	11.43
26-Aug	0	25.4	0	13.97	0	0	0	0
28-Aug	0	0	0	0	17.78	17.78	0	0
Harvest Date	Oct-20				Oct-28			
Total	179.07	171.45	87.63	123.952	93.98	116.84	27.94	92.71

2.3.3 Nitrogen fertilizer application

In this study, a uniform amount of N fertilizer 269 Kg/ha (240 lb./acre) (Urea and ESN) was applied across all four irrigation scheduling methods for all two sites and two years. The University of Minnesota BMPs recommend split applications of N fertilizer for irrigated sandy soils during the corn growing season (Lamb et al., 2015). At S1, a split application of N fertilizer rate 80, 80 and 80 lb./acre (90, 90 and 90 Kg/ha) was conducted at planting, V2 and V8 corn growth stages for both years. At S2, a split application of N fertilizer rate 120 and 120 lb./acre (135 and 135 Kg/ha) was conducted at V2 and V8 corn growth stages for both years. Fertilizer application was followed by an irrigation or rain event to incorporate fertilizer N into the soil.

2.3.4 Volumetric water content measurements

Volumetric water content (VWC) was measured in all study plots at both sites throughout the growing season on a weekly basis using a neutron moisture meter (InstroTek 503 ELITE Hydroprobe). At the beginning of the growing season, metal access tubes were installed in the center row of each plot up to 1.2 m soil depth at S1 and up to 0.75 m depth at S2, due to presence of gravel below 0.75 m depth at S2. The access tubes were covered with a cap to prevent any water from precipitation or irrigation events from going into the tubes. The VWC was measured at intervals of 0.3 m depth at S1 and at intervals of 0.15 m depth at S2. Soil water deficit was calculated based on the VWC readings and irrigation was scheduled based on these measurements in SM treatment. These measurements were also used to conduct a water balance approach for estimating water balance crop evapotranspiration from each treatment.

2.3.5 Water balance ETc estimation

Crop evapotranspiration for all irrigation treatments was estimated using the water balance approach. In a soil-water-plant system change in soil water storage must be equal to the difference between total water inflow to the system and total water outflow from the system. Precipitation (P) and irrigation (I) were considered as inputs to the system as they add water to the system and crop evapotranspiration (ETc), runoff (Rn) and drainage (D) were taken as negative as they take water from the system.

$$dS = P + I - ETc - R - D \tag{5}$$

dS = change in soil water storage (mm)
P = Precipitation (mm)
I = Irrigation applied (mm)
R = Runoff (mm)
D = Drainage (mm)

The change in soil water storage (dS) was calculated from weekly soil water content measurements by the neutron probe. Precipitation amounts were obtained on a daily basis from local weather station data at research sites. Irrigation amounts recommended by different irrigation scheduling methods were used. Runoff was calculated according to the USDA NRCS curve number method for estimating surface runoff (USDA, NRCS, 1985). Drainage values simulated by the EPIC crop growth model were incorporated in this equation. From equation (5), crop evapotranspiration was computed according to the following equation -

$$ETc = P + I \pm dS - R - D \quad (6)$$

Total water application (TWA) in this study is the total amount of water input to the cropping system during the corn growing season, combining precipitation and supplemental irrigation. Seasonal Crop Evapotranspiration (ETc) is the portion of the total water application which is utilized by the crop throughout the growing season. In this study, Percentage Water Use (PWU) is the percentage of total water applied used as crop evapotranspiration and Water Loss (WL) refers to the amount of total water application that was not utilized by the crop and was either lost as deep percolation and runoff or got stored in the soil profile.

$$WL = (TWA - ETc) \quad (7)$$

$$PWU = \{(ETc/TWA) * 100\} \quad (8)$$

TWA - Total water application (mm)
ETc - Crop Evapotranspiration (mm)
PWU - Percentage Water use (mm)
WL - Water Loss (mm)

2.3.6 Soil water nitrate concentrations and load

For the measurement of soil water NO_3 concentration, suction cup lysimeters with porous ceramic cup (100 KPa high flow, Soil Moisture Equipment, Santa Barbara, CA) were installed at depth of 1.2 m approximately 1 week after planting. For installation, a soil auger was used to bore a hole of slightly larger diameter than that of the lysimeter and silica flour slurry was poured at the bottom of the hole to ensure proper hydraulic contact with the soil. Bentonite was added alongside the periphery of the pipe to avoid any preferential flow of water from surface to the suction cup along the periphery of the pipe and soil was poured back after putting the lysimeter in the borehole. Two suction cup lysimeters were installed in the center row of each plot such that they are equidistant from the center of the row, such that representative water samples from both sides of the plot can be obtained. Sampling was done manually by using a hand pump at a suction of 30 KPa to collect soil water draining through the soil at the depth of installation. Samples were collected approximately once a week and samples were kept frozen until analyzed. Drainage values for all plots were simulated from EPIC crop growth model. Nitrate load was then obtained from nitrate concentration field data and simulated drainage from EPIC crop growth model.

2.3.7 Dry matter content and N uptake

Plant, grain and soil samples were collected from each plot at both sites and both growing seasons in order to measure crop biomass and N uptake. The plant samples were collected from each plot at V8, R1 development stages and physiological maturity (R6). A total of six representative plant samples were randomly taken from each plot, three consecutive plants from 2 rows. Whole plant samples were manually cut with knives, passed through a chipper and put in labelled bags. The samples were then dried at 60°C and weighed before being ground by a Thomas Wiley mill. The samples were then sent to the Research Analytical Laboratory (RAL), University of Minnesota for Total-N analysis, where samples were weighed and combusted in an Elementor varioMAX cube to determine Total-N. At harvest, in late October, grain samples were collected from center 4 rows of each plot with 1.5 m end-trimming on either side of the plot with the combine harvester. The grain was oven dried, ground and sent to the Research Analytical Laboratory (RAL) for combustion analysis, for Total-N in grain obtained through the same procedure as above. Post-harvest soil samples were also taken from each plot at soil depths - 0.3 and 0.6 m in order to determine remaining nitrate-N concentration in soil. The samples were collected with the help of a tractor mounted Giddings probe at two depths from the center row of each plot. The soil samples were also ground and sent to the Research Analytical Laboratory (RAL) where Lachat QuickChem 8500 Flow Injection Analyzer was used for Nitrate-N analysis.

2.3.8 Crop yield, crop water use efficiency and irrigation water use efficiency

Corn grain yield was obtained and adjusted to 155 g Kg^{-1} of grain moisture content. In this study, Irrigation Water Use Efficiency (IWUE) is calculated as the amount of corn grain yield (Y_g) produced per unit irrigation water applied (I_a). Crop Water Use Efficiency (CWUE) is calculated as the amount of corn grain yield (Y_g) produced per unit seasonal crop evapotranspiration (ETc).

$$IWUE = Y_g / I_a \quad (9)$$

$$CWUE = Y_g / ETc \quad (10)$$

IWUE – Irrigation water use efficiency (Kg/m^3)
CWUE – Crop water use efficiency (Kg/m^3)

Y_g – Corn grain yield (g/m^2)

I_a – Irrigation applied (mm)

ETc – Seasonal crop evapotranspiration (mm)

2.3.9 Statistical analysis

Data was analyzed with RStudio Version 1.2.1335 (2009-2019 RStudio, Inc.). Analysis of Variance and mixed effect models were used to identify significant differences in parameters of interest – yield, nitrate leaching, crop evapotranspiration and nitrate leaching at $\alpha = 0.05$ across treatments. Irrigation scheduling methods or irrigation treatments were considered as fixed effects while block and year were considered as random effects. Additionally, impact of precipitation was observed on above mentioned crop parameters with year as fixed effect.

2.4 Results and Discussion

2.4.1 Weather

Monthly weather parameters, average temperature and rainfall, are presented in Table 2.5 and Table 2.6 respectively for all site years of the study. Average rainfall and temperature values were obtained from local weather stations established in 2016 for S1 and 2013 for S2 therefore long-term (30 years) mean values were not presented. For S1, the average monthly temperature in Y1 growing season always remained below mean except for the month of September (Table 2.5). Also, monthly rainfall during growing season months was higher than the mean value (Table 2.6). Both lower temperature and higher precipitation reduced irrigation requirements of the crop since most of the crop water need were fulfilled by precipitation. In Y2S1, average temperatures for the months of June, July and August, mid-season months that correspond to higher crop water use and the months that required irrigation, remained higher than the mean value and also total precipitation during Y2 was lower than mean precipitation (Table 2.5 and 2.6). Hence, a greater amount of irrigation 140.53 mm (average for all treatments) was applied in Y2 as compared to that of Y1 (101.66 mm) at S1.

Table 2.5. Monthly and growing season average temperature (℃) for two years (Y1, Y2) at two research sites (S1, S2) in comparison with mean average temperature

Avg. Temp. (℃)	S1			S2		
	Mean (2016-2020)	Y1	Y2	Mean (2015-2020)	Y1	Y2
May	14.41	11.89	13.57	13.31	10.96	12.54
Jun	20.46	19.45	21.58	19.57	18.81	20.89
Jul	22.28	22.17	23.09	21.12	21.19	21.99
Aug	20.31	19.70	20.95	19.11	18.26	20.07
Sep	16.55	17.14	14.52	15.67	16.03	13.47

Oct	7.21	6.41	5.18	6.55	5.18	3.73
Growing season avg.	17.84	17.31	17.72	16.59	16.11	16.16

(Data collected from local weather station at research sites S1 and S2)

Table 2.6. Monthly and growing season rainfall (mm) for two years (Y1, Y2) at two research sites (S1, S2) in comparison with mean rainfall

Rainfall (mm)	S1			S2		
	Mean (2016-2020)	Y1	Y2	Mean (2013-2020)	Y1	Y2
May	84.63	158.24	40.64	87.85	152.40	19.81
Jun	84.48	84.58	99.57	104.78	66.80	71.88
Jul	104.14	105.16	94.74	99.57	105.41	163.83
Aug	110.54	87.12	117.35	95.47	79.76	146.56
Sep	77.57	105.41	25.15	62.07	210.57	22.86
Oct	82.04	101.35	34.54	58.48	74.17	43.94
Growing season total	520.75	632.21	402.08	401.02	538.48	457.20

(Data collected from local weather station at research sites S1 and S2)

For S2, the average growing season mean air temperature (2015-2020) was 16.59 °C and average growing season precipitation (2013-2020) was 401.02 mm. Both Y1 and Y2 growing seasons had higher than average precipitation which amounts to 538.48 mm and 457.20 mm respectively. Hence, lower supplemental irrigation of 32.30 mm and 87.87 mm (average for all treatments) was applied during Y1 and Y2, respectively. Also, for S2, the mean air temperatures for both Y1 (16.11 °C) and Y2 (16.16 °C) growing seasons were slightly lower than the average value (16.59 °C). The irrigation requirement for Y2 were higher than that of Y1 because of higher monthly average temperatures than mean values in the months of June, July and August. These months also correspond to higher crop water use; therefore, supplemental irrigation was required in these months.

2.4.2 Treatment effect on total water application

Total water application is the total amount of water input to the cropping system during the corn growing season, combining precipitation and supplemental irrigation. With different irrigation scheduling methods used, the amount and timing of supplemental irrigation differed among the treatments across the two sites and two growing seasons. It was observed that water required by the crop during early and late season months was totally supplied by the amount of precipitation and almost no supplemental irrigation was required to meet the crop water requirements (Fig 2.1). Hence, total water applied differed only during the months of June, July and August when supplemental irrigation was required to fulfil the crop water demands. In a recent study conducted by Struffert et al. at Westport, MN irrigation was provided only in the months of July and August (Struffert et al., 2016).

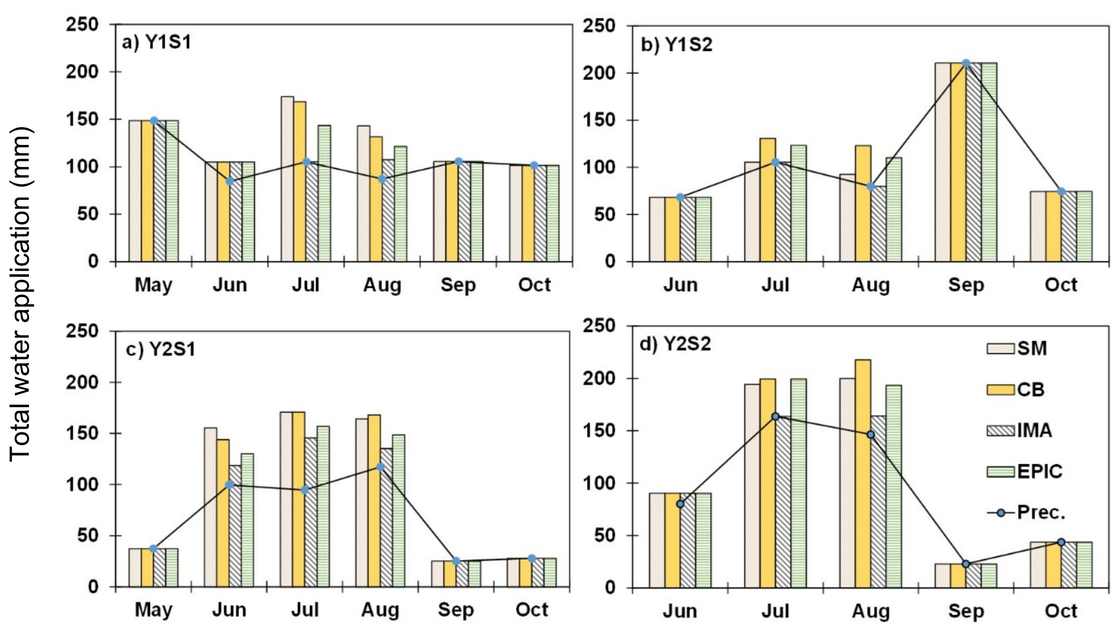

Figure 2.1. Total water application for corn using four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) at two sites (S1, S2)

In Y1S1, lowest total water application was observed in IMA method, which recommended lowest irrigation amounts whereas the highest total water application was observed in SM method which recommended highest irrigation (Table 2.7). IMA based irrigation scheduling consistently maintained highest soil water levels throughout the growing season as compared to other methods at S1. Though the soil water content was maintained between the field capacity and management allowable depletion for the SM method, one possible explanation for highest irrigation recommendation could be that - when irrigation is recommended solely based on soil water status it sometimes does not take into account the changes in water status in the plant and root tissues, which results in inaccurate estimation of crop water requirement and hence inaccurate irrigation recommendations. In a previous study conducted by Sharma and Irmak, irrigation scheduling based on soil moisture monitoring did not take into account the changes in water status in plant and root tissues and created plant water stress even when enough water was available in the soil profile (V. Sharma & Irmak, 2021a).

The growing season precipitation in Y1 at S2 was greater than average growing season precipitation. Hence, the amount of irrigation recommended by each treatment was lower as compared to Y1 at S1 since most of the crop water requirement was fulfilled by precipitation. In Y1S2, the highest total water application was observed under CB method based irrigation scheduling which amounts to 607.06 mm out of which 68.58 mm was irrigation recommended by the treatment (Table 2.7). Again, IMA method of irrigation scheduling resulted in lowest total water application. Total water application in this treatment was from precipitation and no amount of irrigation was recommended. On the other hand, SM, CB and EPIC model based irrigation scheduling recommended 12.70 mm, 68.58 mm and 48.26 mm of irrigation, respectively (Table 2.4). The reason for low or no irrigation recommendation in IMA in Y1 might be due to how it estimates or interpolates precipitation in the model. In the IMA tool, if the precipitation was not overwritten by the user, the interpolation method in the tool tends to overestimate precipitation, thus lowering irrigation recommendation. This was also observed through the soil water content measurements in the IMA plots in Y1S2 that showed soil water content went below the management allowable depletion at certain times in the season.

Table 2.7. Total water application for corn using four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) at two research sites (S1, S2)

Irrigation Treatment	Total Water Application (mm) (Precipitation + Irrigation)				
	Y1S1	Y1S2	Y2S1	Y2S2	Mean
SM	776.99 (632.21 + 144.78)	551.18 (538.48 + 12.70)	581.15 (402.08 + 179.07)	551.18 (457.20 + 93.98)	615.13 a
CB	760.48 (632.21 + 128.27)	607.06 (538.48 + 68.58)	573.53 (402.08 + 171.45)	574.04 (457.20 + 116.84)	628.78 a
IMA	672.85 (632.21 + 40.64)	538.48 (538.48 + 00.00)	489.71 (402.08 + 87.63)	485.14 (457.20 + 27.94)	546.55 b
EPIC	725.17 (632.21 + 92.96)	586.74 (538.48 + 48.26)	526.03 (402.08 + 123.95)	549.91 (457.20 + 92.71)	596.96 a

For each column, values for response variables accompanied by same letters suggest that they are not significantly different ($p<0.05$) from each other

In Y2 at S1, the total water application consistently decreased for all treatments as compared to Y1 due to a substantial decrease in precipitation amount (~230 mm) from Y1 (632.21 mm) to Y2 (402.08 mm) (Table 2.4). Also decrease in precipitation resulted in higher irrigation recommendations for all treatments (SM, CB, IMA and EPIC) in Y2 (179.09, 171.45, 87.63 and 123.95 mm) as compared to that of Y1 (144.78, 128.27, 40.64 and 92.96 mm) (Table 2.4). Although the decrease in precipitation amounts in Y2 resulted in higher irrigation recommendations for all treatments, irrigation was still recommended in the months of June, July and August (same as Y1) (Fig 2.1 a and c). This is because precipitation amounts in all the four site-years were able to fulfil crop water requirements estimated by all four irrigation treatments in the months of May, September and October when crop water requirements are lower but not in the months of June, July and August when crop water requirements are at their peak (Fig 2.1). In Y2S1, the highest total water application again occurred in SM based irrigation scheduling and lowest total water application was observed in IMA method as in Y1S1 (Table 2.7). Hence, for both growing seasons of the study at S1, SM based irrigation scheduling resulted in highest irrigation recommendation and IMA based irrigation scheduling resulted in lowest irrigation recommendation.

In Y2 at S2, highest total water application was observed in CB method of irrigation scheduling which amounts to 574.04 mm out of which 116.84 mm is irrigation recommended by the treatment (Table 2.7). The lowest irrigation recommendation (27.94 mm) and total water application was observed under IMA method of irrigation scheduling. For both growing seasons (Y1 and Y2) for S2, the highest and lowest irrigation recommendations were observed in CB method and IMA method of irrigation scheduling, respectively.

On average for all four site-years of the study, the CB method of irrigation scheduling resulted in 15% more total water application as compared to IMA based irrigation scheduling. The IMA based irrigation scheduling method resulted in significantly lower total water application for all four site-years of the study (Table 2.7). Therefore, the results of the study suggest that total water application or irrigation application (since precipitation is constant for all treatments) can be significantly different based on which irrigation scheduling method is being used for corn crop in coarse textured soils.

2.4.3 Treatment effect on seasonal crop evapotranspiration (ETc)

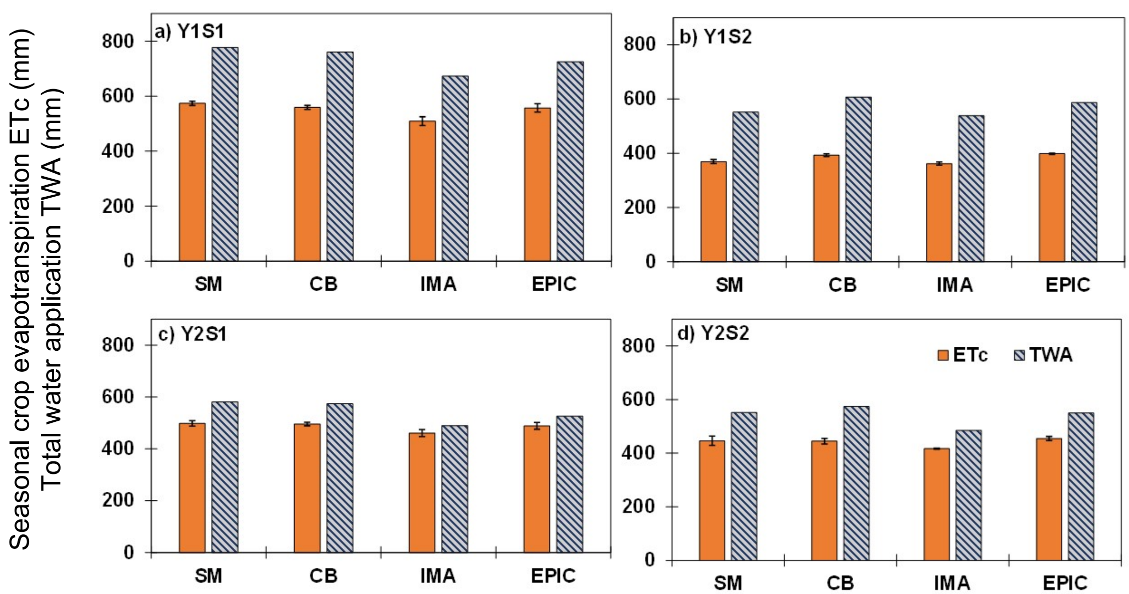

Figure 2.2. Seasonal crop evapotranspiration and total water application for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for (a) Year 1 and Site 1 (Y1S1), (b) Year 1 and Site 2 (Y1S2), (c) Year 2 and Site 1, and (d) Year 2 and Site 2

In a soil-water-plant system, total water inflow to the system is through precipitation and irrigation and outflow from the system occurs in the form of crop evapotranspiration and water losses (mainly comprising of deep percolation and runoff). Seasonal Crop Evapotranspiration (ETc) is the portion of the total water application which is utilized by the crop throughout the growing season. In this study, Percentage Water Use (PWU) is the percentage of total water applied used as crop evapotranspiration and Water Loss (WL) refers to the amount of total water application that was not utilized by the crop and was either lost as deep percolation and runoff or got stored in the soil profile. Maize seasonal ETc (determined from soil water balance) total water application for each treatment and site-year is presented in Figure 2.2. In general, the ETc increased with increasing irrigation (Figure 2.3) and varied from 509 to 574 mm, 362 to 398 mm, 461 to 498 mm and 416 to 454 mm in Y1S1, Y1S2, Y2S1 and Y2S2, respectively (Table 2.8). Substantial variation in ETc between years and sites was observed.

Table 2.8. Seasonal crop evapotranspiration (ETc) for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) and two research sites (S1, S2)

Irrigation treatment	Seasonal crop evapotranspiration (mm)			
	Y1S1	Y1S2	Y2S1	Y2S2
SM	574.20 ± 7.88 a	369.48 ± 7.06 b	498.21 ± 10.52 a	445.82 ± 17.40 a
CB	559.33 ± 7.18 a	392.96 ± 4.86 a	495.66 ± 6.89 a	444.39 ± 10.71 a
IMA	509.48 ± 15.93 b	361.88 ± 5.94 b	460.60 ± 13.75 b	416.50 ± 2.06 b
EPIC	557.49 ± 15.36 a	398.41 ± 2.19 a	488.32 ± 12.84 a	454.35 ± 8.05 a

For each column, values for response variables accompanied by same letters suggest that they are not significantly different ($p<0.05$) from each other

Table 2.9. Water loss for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) and two research sites (S1, S2)

Irrigation treatment	Water loss (TWA – ETc) WL (mm)			
	Y1S1	Y1S2	Y2S1	Y2S2
SM	202.79	181.70	82.94	105.36
CB	201.15	214.10	77.87	129.65
IMA	163.37	176.60	29.12	68.64
EPIC	167.68	188.33	37.72	95.56

Table 2.10. Percentage water use (PWU) for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) and two research sites (S1, S2)

Irrigation treatment	Percentage water use {(ETc/TWA) *100} PWU (%)			
	Y1S1	Y1S2	Y2S1	Y2S2
SM	73.90	67.03	85.73	80.89
CB	73.55	64.73	86.42	77.41
IMA	75.72	67.20	94.05	85.85
EPIC	76.88	67.90	92.83	82.62

Table 2.11. Seasonal Crop Evapotranspiration, Total Water Application and Water Loss for four different irrigation scheduling methods (SM, CB, IMA, EPIC) averaged for two years (Y1, Y2) and two research sites (S1, S2)

Irrigation treatment	Total water application (mm)	Seasonal crop ET (mm)	Water loss (mm)	PWU (%)
SM	615.13 a	471.93 a	143.20 ab	76.89 b
CB	628.78 a	473.08 a	155.69 a	75.53 b
IMA	546.55 b	437.11 b	109.43 c	80.71 a
EPIC	596.96 a	474.64 a	122.32 bc	80.06 a

For each column, values for response variables accompanied by same letters suggest that they are not significantly different ($p<0.05$) from each other

In Y1S1, SM method and CB method based irrigation scheduling resulted in 202.79 mm and 201.15 mm of water loss respectively (Table 2.9). The irrigation amounts and timings estimated by IMA tool and EPIC model reduced water loss to 163.37 mm and 167.68 mm respectively (Table 2.9). Therefore, for IMA and EPIC model based irrigation scheduling a higher percentage – 75.72% and 76.87 % of total water application was utilized by crop in the form of crop evapotranspiration respectively (Table 2.10). Although, the EPIC model based irrigation scheduling resulted in highest PWU – 76.88 %, SM based irrigation scheduling resulted in highest crop evapotranspiration due to higher irrigation recommendations in the SM method. The IMA method of irrigation scheduling had the lowest irrigation recommendations and therefore resulted in significantly lower ETc than other irrigation scheduling methods (Table 2.8).

In Y1S2 (Fig 2.2 b), higher than average precipitation was received at S2 and most of the crop water requirements were fulfilled by precipitation itself and a small amount of irrigation was recommended by irrigation scheduling methods. In fact, for IMA based irrigation scheduling no irrigation was recommended. Therefore, for S2, water losses in Y1 were higher than Y2 (Table 2.9). Both IMA and SM method had significantly lower crop evapotranspiration due to lower irrigation recommendations. PWU for Y1S2 was also lower than all other site years for all irrigation treatments and for CB method of irrigation scheduling only 64.73% of water was utilized by the crop (Table 2.10). Over estimation of irrigation requirement by the CB method is suggested by the results since it recommended 69 mm of irrigation in Y1S2 when about 214.10 mm of water was lost to deep percolation and runoff (Table 2.9). However, the IMA method of irrigation scheduling reduced water loss to 176.60 mm by not recommending any irrigation. Though it is possible that no irrigation in the IMA method might have induced some water stress in the crop. Also, in this study an older neutron probe (Troxler 4302) was used for taking soil moisture measurements in Y1 at S2, which resulted in flawed soil moisture readings. Therefore, for Y1S2 water-balance ETc calculations it was assumed that the soil water levels were equal to field capacity at beginning and end of growing season and change in soil water storage was assumed to be zero. From visual observations of soil in the beginning and end of growing season at S2 the soil looked wet and close to field capacity.

In Y2S1 (Fig 2.2 c), maximum PWU and minimum WL were observed for all treatments as compared to other site years (Tables 2.9 and 2.10). The SM, CB, IMA and EPIC method based irrigation scheduling had a PWU of 85.73 %, 86.42 %, 94.05 %, and 92.83 %, respectively. It is important to note that for S1, the precipitation amount reduced from 632 mm in Y1 to 402 mm in Y2 which contributed to an overall increase in PWU. Higher percentage water use was observed in IMA and EPIC model based irrigation scheduling because these methods were able to reduce water loss to as low as 29.12 and 37.32 mm respectively for the Y2 growing season at S1. The results suggested that since irrigation recommendation was least in IMA, it significantly impacted ETc, however, both IMA and EPIC method had maximum PWU in all site years indicating higher water use efficiency (Table 2.10) for these treatments.

In Y2S2 (Fig 2.2 d), an increase in crop evapotranspiration was observed as compared to Y1S2 for all irrigation treatments. EPIC model based irrigation scheduling resulted in maximum crop evapotranspiration of 454.35 mm (Table 2.8). Water loss was observed to be maximum in CB method based irrigation scheduling which amounts to 129.65 mm. Again, a significantly lower ETc was observed in IMA based irrigation scheduling. On average, the IMA method of irrigation scheduling, which resulted in significantly lower total water application (Table 2.11), also resulted in significantly lower seasonal crop evapotranspiration as compared to other irrigation scheduling methods across all sites and years (Table 2.11).

Relationship between seasonal irrigation and seasonal crop evapotranspiration is presented in Figure 2.3. For all site-years the ETc curves flatten or even diminish at higher irrigations indicating that after a certain irrigation amount, adding more water into the system would not contribute towards increasing the ETc. For each site-year, high correlation between seasonal irrigation amounts and seasonal crop evapotranspiration was observed and R^2 values ranged from 0.95 in Y1S2 to 0.99 in Y2S1 for individual site years. While for data averaged across years and sites, seasonal irrigation amounts and seasonal ETc had lower R^2 value of 0.51. The lower R^2 value for the mean data may be due to the inclusion of other weather variables including temperature, precipitation, solar radiation and wind speed which may impact ETc other than irrigation amounts (S. Irmak, 2015). Comparing all site-years, the highest ETc was observed in Y1 at S1 whereas the lowest ETc was observed in the same year at S2 (Fig 2.3).

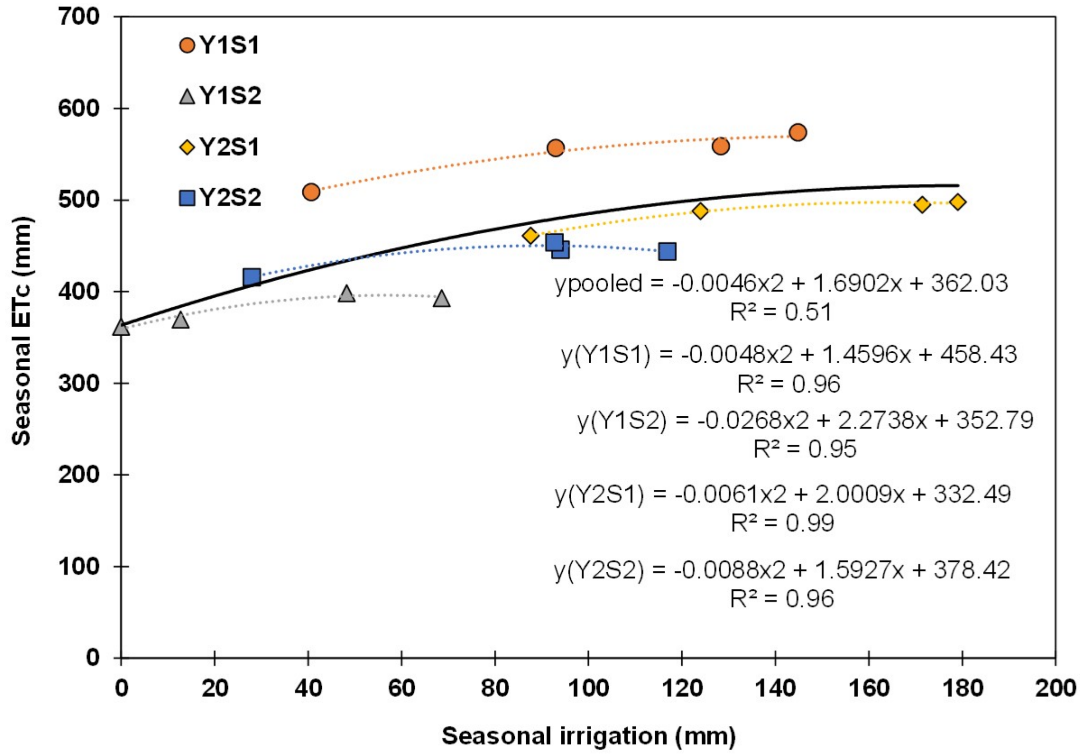

Figure 2.3. Relationship between seasonal irrigation amounts and seasonal maize crop evapotranspiration ETc for two years (Y1, Y2) and two research sites (S1, S2)

Overall, IMA method of irrigation scheduling resulted in significantly lower crop evapotranspiration for all site years of the study individually (for Y1S2 both IMA and SM had significantly lower ETc) and also on average for all site-years together (Table 2.8 and 2.11). This was because the IMA tool recommended lowest irrigation amounts consistently across all site-years as compared to other treatments. Similar results were obtained in a recent study by Sharma and Irmak, minimum crop evapotranspiration in corn was observed in lowest irrigation or no irrigation treatment (V. Sharma & Irmak, 2021b). Maximum PWU was observed for the EPIC method in Y1 and for IMA based irrigation scheduling in Y2 at both sites.

Both the IMA and EPIC methods resulted in significantly higher PWU on average for all site-years of the study.

2.4.4 Treatment effect on Soil Water Dynamics

Irrigation management, fundamentally, is the process of maintaining soil water content at a certain level such that crop does not experience water stress in the root zone of the crop. Ideal range for soil water content is between Field Capacity (FC) and Maximum Allowable Depletion (MAD). The soil water content should never reach Permanent Wilting Point (PWP) level as that may lead to stressed crops or yield reduction. The soil water content for each site and year for four treatments is presented in Figure 2.3. In general, for all four irrigation methods, a similar trend of rise and fall of soil water content was observed, since irrigation scheduling method (amount and timing of irrigation) used was the only variable and other factors that may affect soil water content (i.e., solar radiation, temperature, wind speed, humidity, rainfall, crop type, crop growth stage) were constant for a particular site year. In the beginning of the growing season, when crop is less sensitive to crop water stress, MAD was kept at 55-60% of Available Water Holding Capacity (AWHC). In mid-season, as the crop reaches critical growth stage and enters its usual peak water use period MAD was decreased to 40-45% of AWHC. Finally, in late-season months, the MAD values were increased back to 55-60% of AWHC when the crop reached maturity.

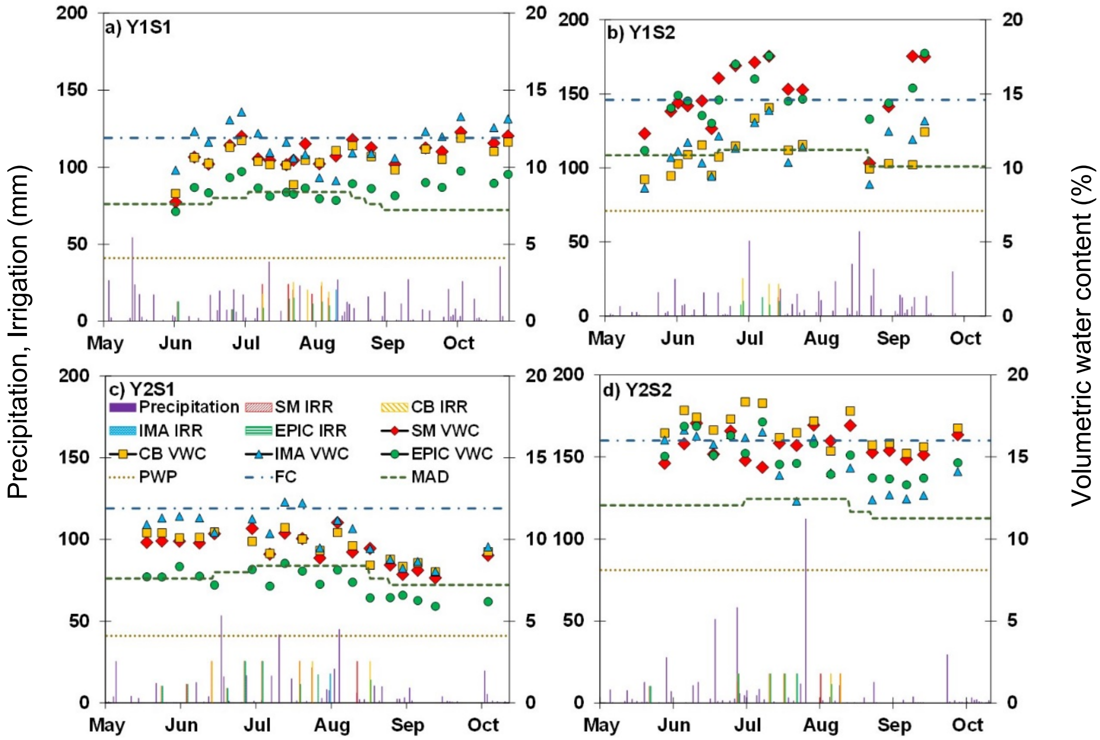

Figure 2.4. Soil water content (VWC %) for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for (a) Year 1 and Site 1 (Y1S1), (b) Year 1 and Site 2 (Y1S2), (c) Year 2 and Site 1 (Y2S1), and (d) Year 2 and Site 2 (Y2S2) using neutron probe

In Y1S1 (Fig 2.4 a), all four irrigation scheduling methods were able to maintain soil water content above Maximum Allowable Depletion (MAD) except for the EPIC crop growth model based irrigation scheduling for which soil water content went slightly below MAD. Due to more frequent and smaller amounts of irrigation in EPIC, the soil moisture went slightly below the MAD value in the peak ETc periods as crop was effectively using all the irrigation water applied at the right time (Table 2.3). The IMA method for irrigation scheduling maintained highest soil water content mostly later in the growing season (Fig 2.4 a). This could possibly be attributed to lower irrigations in the mid-season by IMA method that might have impacted the crop growth (biomass and leaf area index) that resulted in lower ETc and higher soil water.

In Y1S2 (Fig 2.4 b), crop water requirements were lower due to higher than average precipitation and lower than average temperature. Hence, lowest irrigation was recommended on average among all four site years for Y1S2. As most of the crop water requirement was fulfilled by precipitation soil water level differences among treatments should have been minimum. Still, the soil water levels among all irrigation treatments differed a lot as compared to other site years (Fig 2.4). Also, up to July 14, no difference in total water application occurred since only one irrigation event happened before July 14 and that was on June 11 in which 10.16 mm of irrigation was equally applied to all treatments to incorporate urea fertilizer. This discrepancy in the soil water levels for all treatments in Y1S2 might have developed from the use of an older neutron probe (Troxler 4302) at S2 during the Y1 growing season for the measurement of soil water levels. Comparing soil water at the peak growing season when irrigation was applied, soil water followed the same trend as irrigation. The soil moisture was lowest in the IMA plots where no irrigation was applied whereas the higher soil water was observed in SM and EPIC plots. The CB plot had the highest irrigation however, the soil water was lower than SM and EPIC treatments indicating water being used either as ETc or WL. Though it is clear from Table 2.9 that maximum water losses occurred in CB in Y1S2 which shows that excessive irrigation not always helps in increasing the ETc and may contribute to deep percolation losses.

In Y2S1 (Fig 2.4 c), soil water levels for all irrigation scheduling methods remained between FC and MAD except for EPIC crop growth model based irrigation scheduling. The EPIC model based irrigation scheduling recommended 123.95 mm of irrigation which resulted in TWA of 526.03 mm (Table 2.7). Out of 526.03 mm of TWA more than 92% was utilized in Crop Evapotranspiration (ETc) (Table 2.10). As more than 92% of water applied was utilized by the crop, the soil water level dropped below the MAD. The IMA tool based irrigation scheduling had the highest soil water levels in Y2S1, which again can be attributed to lower irrigations in the mid-season by IMA method that might have impacted the crop growth (biomass and leaf area index) that resulted in lower ETc and higher soil water.

In Y2S2 (Fig 2.3 d), the CB method of irrigation scheduling consistently maintained higher soil water levels as compared to other irrigation methods and it was also the method that recommended highest irrigation in Y2S2 indicating that CB method of irrigation scheduling overestimated crop water requirements and recommended higher irrigation which kept soil water levels above field capacity for a large part of the growing season (Fig 2.3 d). SM, IMA and EPIC model based irrigation scheduling were able to maintain soil water levels between FC and MAD for most of the growing season. In case of IMA based irrigation scheduling, soil water level went below MAD during mid-season when a lower MAD value – 45% of AWHC was chosen.

2.4.5 Treatment effect on Crop N uptake

Most irrigated sandy soils used for corn production in Minnesota are very productive (Struffert et al., 2016) but require nutrient and water applications for most economical production (Lamb et al., 2015). Nitrogen supplied through fertilizer applications may leach below the root zone of the crop with excess water in the form of nitrates (NO^{3-}) as nitrate is readily dissolved in and carried by water. Therefore, constant monitoring of nutrient uptake, especially N, is required. Nitrogen loss not only limits the amount of N available for crop uptake but also is an environmental concern. N uptake by corn at R1 and R6 corn growth stages at all four site years of the study is presented in Table 2.12. In all years and sites no significant differences were observed in N uptake between irrigation treatments. This might suggest that ETc was not limited by water application and all irrigation treatments recommended enough irrigation to maintain the ET required for crop production and hence N uptake was not significantly impacted at R1 and R6 corn growth stages.

The relationship between corn N uptake at physiological maturity (R6) and PWU is presented in Figure 2.5. Though not significant, a positive relationship of PWU and N uptake was observed for three site years except Y1S2 in the study (Figure 2.5). In Y1S1, highest N uptake at physiological maturity (R6 stage) was observed in the EPIC method of irrigation scheduling and this was the method in which the highest percentage water use was observed among other treatments in Y1S1 (Table 2.10 and 2.12). Also, lowest N uptake at R6 growth stage for Y1S1 was observed in CB method of irrigation scheduling and this was the same method which had the lowest percentage water use for Y1S1 (Table 2.10 and 2.12). In Y2S1, the lowest PWU was observed in SM that has the lowest N uptake whereas both EPIC and IMA has higher N uptake and higher PWU. Similarly, in Y2S2, a positive relationship between PWU and N uptake was observed. Previous studies have also observed positive relationship between water use and N uptake (Muschietti-Piana et al., 2018; Quemada Miguel, 2016).

Table 2.12. Comparison of mean N uptake for corn across four different irrigation scheduling methods (SM, CB, IMA, EPIC) at R1 and R6 growth stages for two years (Y1, Y2) at two research sites (S1, S2)

Year	Site	Corn growth stage	N uptake (Kg/ha)			
			SM	CB	IMA	EPIC
Y1	S1	R1	105.78 a	171.26 a	133.67 a	155.59 a
		R6	170.50 a	142.01 a	170.11 a	180.92 a
	S2	R1	163.62 a	137.78 a	157.78 a	121.78 a
		R6	184.50 a	233.43 a	209.49 a	203.84 a
Y2	S1	R1	139.61 a	152.71 a	124.50 a	164.97 a
		R6	196.37 a	218.21 a	211.99 a	219.90 a
	S2	R1	166.93 a	194.09 a	162.00 a	190.28 a
		R6	197.34 a	197.33 a	195.38 a	182.91 a

N uptake (Kg/ha) values in the same row accompanied by the same letter are not significantly different ($p<0.05$) from each other

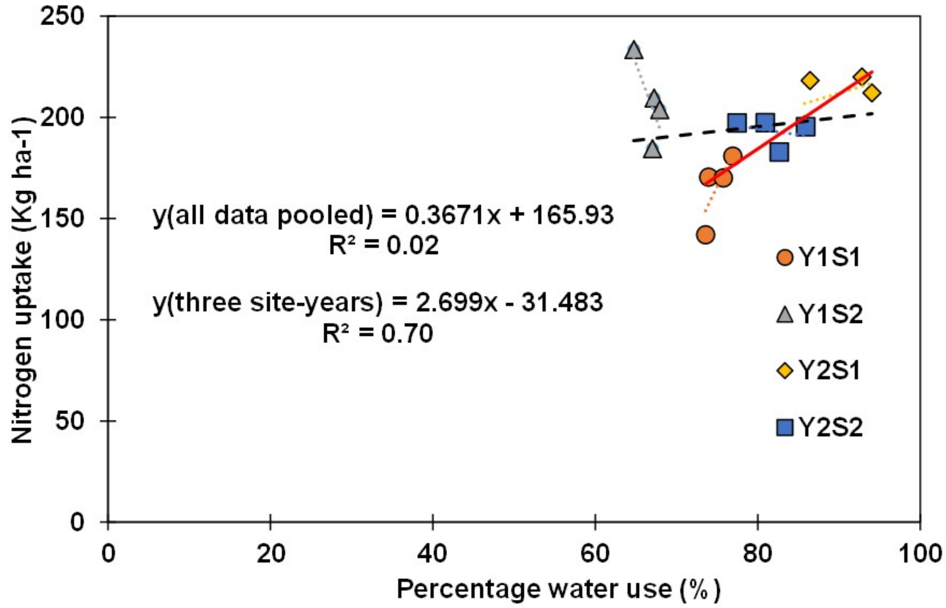

Figure 2.5. Relationship of percentage water use (PWU) with nitrogen uptake for four site years (Y1S1, Y1S2, Y2S1, and Y2S2); the black dotted line indicates relationship of all the site years' mean data and red solid line indicates the relationship for three-site years (Y1S1, Y2S1 and Y2S2)

However, in Y1S2, the CB method of irrigation scheduling resulted in maximum N uptake at physiological maturity (Table 2.12). Although it had lowest PWU, this treatment received maximum amount of irrigation and total water application (Table 2.3 and 2.10). Also, the CB method (and EPIC method) had significantly higher crop evapotranspiration for Y1S2. Hence, availability of more water to crop and its translation to higher crop evapotranspiration might be the reason behind higher N uptake in the CB method treatment. Similarly, in Y2S2 maximum N uptake at R6 stage is observed in both SM and CB method based irrigation scheduling and these two methods recommended highest irrigation in Y2S2 (Table 2.7 and 2.12).

In general, as corn grows and advances towards higher growth stages, it accumulates more N in above ground biomass and hence total N (grain + stover) in plant biomass increases with increase in growth stage. In this study an increase in total N was observed from R1 to R6 growth stages for almost all treatments across all site years of the study. Although, unexpectedly, a decrease in N uptake was observed in CB method from R1 to R6 stage in Y1S1 and in EPIC method from R1 to R6 stage in Y2S2 (Table 2.12). This irregularity in N uptake may be attributed to small sample size of 6 plants per plot.

Significant difference ($p<0.05$) was observed while comparing the N uptake at physiological maturity stage (R6) in the year Y1 with that of Y2 at S1. This can be attributed to a large difference in amount of total growing season precipitation from Y1 to Y2 corn growing seasons at the site S1 (Table 2.6). The precipitation decreased from 632 mm in Y1 to 402 mm in Y2 corn growing season. Therefore, the study suggests that a large change in total water application (precipitation amount), may result in a significant difference in N uptake regardless of irrigation scheduling treatment applied.

2.4.6 Treatment effect on Nitrate Leaching

N fertilizer applied to crop undergoes mineralization and forms nitrate ions (NO^{3-}) which can be readily dissolved and carried by water. Some nitrate-N is taken up by the crop from its root zone and rest of negatively charged nitrate ions (NO^{3-}) get repelled by negatively charged soil particles and leach with drainage water. Nitrate concentrations in soil water samples varied from 0.1 mg/l to 210 mg/l across all four site years of the study.

In this study maximum growing season nitrate leaching was observed in summer months from June to August which coincides with the time of supplemental irrigation applied and eventually higher total water application (Figure 2.6). Total growing season nitrate-N leaching varied from 4.5 Kg/ha to 46 Kg/ha with the minimum nitrate leaching (4.5 Kg/ha) occurring in the year Y2 for IMA irrigation scheduling treatment at S1 and the maximum nitrate leaching for CB (46 Kg/ ha) irrigation treatment in Y1 at the same site S1 (Fig. 2.6 a and c).

In Y1S1 (Fig. 2.6 a), although, highest total irrigation amount (144.78 mm) was recommended by SM method of irrigation scheduling (Table 2.3), CB method of irrigation scheduling resulted in maximum nitrate leaching (Table 2.13). This is because N uptake at physiological maturity (R6) for SM was greater than CB method of irrigation scheduling (Table 2.12). Hence, for SM based irrigation scheduling lower nitrate-N was available that potentially could be lost to nitrate leaching. Also, the differences in N-uptake and nitrate leaching between SM and CB methods may have been influenced by irrigation timing. Though both of them had similar seasonal irrigation amount, the timing of irrigation was not the same. The EPIC model and IMA based irrigation scheduling on the other side recommended lower irrigation amounts and resulted in lower nitrate leaching (Table 2.3 and 2.13). Other studies have also observed reduction in nitrate leaching with reduction in irrigation amounts (Bohman et al., 2020; Sigua et al., 2016). No significant difference ($p<0.05$) in nitrate leaching was observed among irrigation treatments in Y1S1.

In Y1S2 (Fig 2.6 b), precipitation amounts were a lot higher than average for the region so least irrigation amounts were recommended by each treatment as compared to other site years. The CB method of irrigation scheduling resulted in significantly higher nitrate leaching (Table 2.13) and this was also the method with highest irrigation amounts (Table 2.7). In Y2S2 (Fig 2.6 d), EPIC model based irrigation scheduling resulted in significantly higher nitrate leaching as compared to IMA, and higher nitrate leaching as compared to CB and SM (Table 2.13). This is because the N uptake at physiological maturity (R6) for EPIC method was least in Y2S2 (Table 2.12). Also, the IMA method of irrigation scheduling resulted in lowest nitrate leaching as compared to other treatments, this can be attributed to its lowest irrigation recommendations. Both N uptake and irrigation amount have been observed to impact nitrate leaching. Nitrate leaching increased with increase in irrigation amounts and decreased with increase in N uptake.

Table 2.13. Nitrate-N leaching for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) at two sites (S1, S2)

Irrigation Treatment	N leaching (Kg/ha)				
	Y1S1	Y1S2	Y2S1	Y2S2	Mean
SM	38.17 ± 11.59 a	14.28 ± 4.00 b	5.72 ± 0.20 a	40.47 ± 20.51 ab	24.66 ± 14.99 ab
CB	46.84 ± 2.53 a	27.49 ± 2.21 a	8.07 ± 1.71 a	37.44 ± 14.11 ab	29.96 ± 14.37 a
IMA	26.68 ± 5.26 a	14.77 ± 2.09 b	4.54 ± 1.80 a	19.00 ± 2.34 b	16.25 ± 7.99 b
EPIC	33.41 ± 7.29 a	16.52 ± 6.82 b	6.99 ± 2.46 a	45.70 ± 20.50 a	25.65 ± 14.95 ab

For each column, values for response variables accompanied by same letters suggest that they are not significantly different from each other

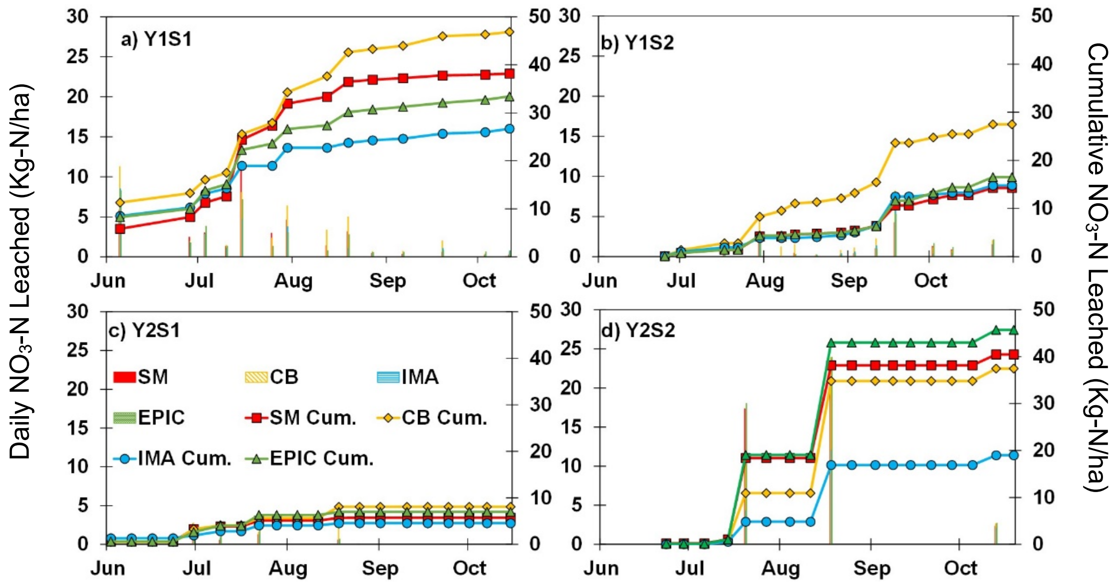

Figure 2.6. Nitrate-N leached for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) at two research sites (S1, S2)

In this study, the CB method of irrigation scheduling resulted in maximum cumulative nitrate leaching for S1 and S2 across Y1 and Y2 growing seasons on an average. This can be explained by the fact that this method had highest irrigation recommendations and had significantly higher water losses (Table 2.11). The IMA method gave the lowest irrigation recommendations and resulted in significantly lower nitrate leaching. According to previous studies, both irrigation and precipitation events increase nitrate leaching, especially on sandy soils (Maharjan et al., 2014). Since the N fertilizer application rate was kept constant for each treatment, higher irrigation amounts and higher water losses may be the major factor responsible for higher nitrate leaching.

Although the irrigation treatments had no significant differences in measured N uptake, the CB method and IMA method of irrigation scheduling resulted in significantly higher and lower nitrate leaching on an average for all site-years, respectively (Table 2.13). Therefore, the results of the study suggested that irrigation scheduling methods can significantly impact nitrate leaching without significantly impacting nitrogen uptake. Many studies have demonstrated a reduction in nitrate leaching with reduced irrigation (Bohman et al., 2020; Sigua et al., 2016). Some studies also found that impact of irrigation is more prominent on nitrate leaching than N application rate (Pang et al., 1998).

Precipitation was also a major factor influencing nitrate leaching. Precipitation at S1 decreased from 632 mm in Y1 to 402 mm in Y2 which resulted in an 83% overall reduction in the total nitrate leaching from the site across all treatments without significantly impacting corn yield. This is in agreement with previous studies, in which precipitation events were one of the major factors that have influenced nitrate leaching (Meisinger & Ricigliano, 2017). Additionally, Wang et al. observed that maximum nitrate leaching happened after precipitation events and irrigation had more prominent effect on nitrate leaching during dry years (Wang et al., 2014). In this study, both irrigation scheduling and precipitation impacted nitrate leaching. Impact of precipitation was more prominent at S1 and that of irrigation scheduling at S2.

Also, post-harvest soil residual nitrate concentrations for 0-0.6 m soil depth had no significant difference among irrigation treatments on average for all site-years.

2.4.7 Treatment effect on Corn Grain Yield and Water Use Efficiency

Prior research has found that crop water stress is critical to corn growth and hence appropriate irrigation scheduling is necessary to obtain ideal yields (El-Hendawy & Schmidhalter, 2010; Stone et al., 2010). In this study, impact of irrigation scheduling (amount and timing of irrigation) was observed on corn grain yield in coarse textured soils. A similar study conducted by Sigua et al. compared the impact of three irrigation scheduling methods on corn yield and nitrate leaching in low water holding capacity soils and found that yield was not impacted by the type of irrigation scheduling method used (Sigua et al., 2016). Similar results were obtained in our study, corn grain yield was not significantly impacted by total irrigation water applied or the irrigation scheduling method used. Even the IMA method of irrigation scheduling which resulted in the lowest total water applied consistently in all site years of the study obtained the corn yields which were not significantly different than other treatments. In general, treatments with low irrigation rates exhibited the highest IWUE and vice-versa in all seasons and sites which is in agreement with Payero et al. (2009). This decreasing trend can be expected in the regions or situations where grain yield is positive at zero irrigation (rainfed conditions) such as Minnesota, however, in the regions or situations where no yield could be obtained without irrigation, increase in irrigation would increase IWUE (Payero et al., 2009).

In Y1S1, no significant difference for corn grain yield was observed among treatments. Highest corn grain yield was obtained with EPIC method of irrigation scheduling which is not the method with highest irrigation recommendation (Table 2.14). Both CB and SM methods recommended higher irrigation amounts but the EPIC method performed better in calculating crop water requirements and recommending irrigation amounts more appropriate to crop needs and minimized the number of days with water stress. For all irrigation events in Y1S1, the maximum irrigation applied in a single irrigation event for SM (24.33 mm) and CB (25.4 mm) was greater than EPIC crop growth model (15.24 mm). This may be attributed to overestimation of irrigation requirements by SM and CB methods. Also studies show that reduction in irrigation efficiency is mainly due to deep percolation (Bouwer, 1994). Hence, reduced irrigation efficiency may lead to enhanced nitrate leaching (with increased deep percolation) and lower water and N available for uptake which may ultimately translate to lower crop yield. EPIC method resulted in higher yield with lower irrigation amounts (and higher IWUE and CWUE) which indicates better performance of the EPIC crop growth model in estimating crop water requirements in Y1S1.

Again, in Y1S2, corn grain yield was not significantly impacted by irrigation treatment and highest corn grain yield (11.61 Mg/ha) was obtained by EPIC model based irrigation scheduling, followed by CB, SM and IMA (11.56, 11.35 and 11.23 Mg/ha respectively) methods (Table 2.14). The CB method recommended higher irrigation amounts than EPIC model, but the CWUE for EPIC was highest in Y1S2 as compared to all other scheduling methods. The SM and IMA methods for irrigation scheduling had lower irrigation recommendations than CB and EPIC. In fact, the IMA method did not recommend any irrigation throughout the growing season for Y1S2. Both these methods had lower corn grain yield as compared to EPIC and CB method.

Table 2.14. Seasonal crop evapotranspiration, total water application, corn grain yield, irrigation water use efficiency (IWUE) and crop water use efficiency (CWUE) for four different irrigation scheduling methods (SM, CB, IMA, EPIC) for two years (Y1, Y2) at two sites (S1, S2)

Site-years	Irrigation Treatment	Corn Grain Yield (Mg/ha)	TWA (P + I) (mm)	ETc (mm)	IWUE (Kg/m^3)	CWUE (Kg/m^3)
Y1S1	SM	12.39 ± 0.67 a	776.99 (632.21 + 144.78)	574.20 ± 7.88 a	8.56 ± 0.38	2.16 ± 0.08
	CB	11.86 ± 0.38 a	760.48 (632.21 + 128.27)	559.33 ± 7.18 a	9.25 ± 0.24	2.12 ± 0.05
	IMA	11.49 ± 1.21 a	672.85 (632.21 + 40.64)	509.48 ± 15.93 b	28.28 ± 2.44	2.26 ± 0.25
	EPIC	12.55 ± 0.44 a	725.17 (632.21 + 92.96)	557.49 ± 15.36 a	13.50 ± 2.25	2.25 ± 0.11
Y1S2	SM	11.35 ± 0.33 a	551.18 (538.48 + 12.70)	369.48 ± 7.06 b	89.34 ± 2.11	3.07 ± 0.04
	CB	11.56 ± 0.74 a	607.06 (538.48 + 68.58)	392.96 ± 4.86 a	16.86 ± 0.88	2.94 ± 0.13
	IMA	11.23 ± 0.75 a	538.48 (538.48 + 00.00)	361.88 ± 5.94 b	-	2.82 ± 0.14
	EPIC	11.61 ± 0.50 a	586.74 (538.48 + 48.26)	398.41 ± 2.19 a	24.05 ± 0.85	3.21 ± 0.07
Y2S1	SM	11.35 ± 0.66 a	581.15 (402.08 + 179.07)	498.21 ± 10.52 a	6.34 ± 0.30	2.28 ± 0.13
	CB	12.23 ± 0.46 a	573.53 (402.08 + 171.45)	495.66 ± 6.89 a	7.13 ± 0.22	2.47 ± 0.10
	IMA	11.76 ± 0.33 a	489.71 (402.08 + 87.63)	460.60 ± 13.75 b	13.43 ± 0.31	2.56 ± 0.12
	EPIC	11.80 ± 1.03 a	526.03 (402.08 + 123.95)	488.32 ± 12.84 a	9.52 ± 0.68	2.42 ± 0.21
Y2S2	SM	10.71 ± 0.40 a	551.18 (457.20 + 93.98)	445.82 ± 17.40 a	11.40 ± 0.34	2.41 ± 0.15
	CB	10.91 ± 0.36 a	574.04 (457.20 + 116.84)	444.39 ± 10.71 a	9.34 ± 0.25	2.45 ± 0.05
	IMA	10.48 ± 0.87 a	485.14 (457.20 + 27.94)	416.50 ± 2.06 b	37.49 ± 2.55	2.51 ± 0.17
	EPIC	10.67 ± 0.18 a	549.91 (457.20 + 92.71)	454.35 ± 8.05 a	11.51 ± 0.16	2.35 ± 0.06

For each column, values for response variables for each site year accompanied by same letters suggest that they are not significantly different ($p<0.05$) from each other

Also, in Y2S1, no significant difference in yield was observed among irrigation treatments. The CB method based irrigation scheduling resulted in maximum yield among all other treatments which also recommended the highest irrigation (Table 2.14). Also, in Y2S1, CB method based irrigation scheduling resulted in maximum yield as compared to other treatments. But here the SM method recommended higher irrigation (179.07 mm) than that of CB method (171.45 mm) but better performance of CB method was observed because it resulted in higher IWUE and CWUE than the SM method of irrigation scheduling. Therefore, greater yields were obtained in CB method than SM method based irrigation scheduling. Even the EPIC model and IMA tool based irrigation scheduling produced higher yield than SM method based irrigation scheduling, both the methods had far lower irrigation recommendations than SM method. The results suggest that not only irrigation amounts but also CWUE and IWUE influence corn yield.

No significant difference in corn yield was observed among irrigation scheduling treatments on average for all site years of the study. For Y1, the EPIC model resulted in highest yield at both the research sites, irrespective of the lower irrigation amounts than other treatments. The highest irrigation amounts at S1 were recommended by SM method (145 mm) which was almost 56% greater than that of EPIC treatment (93 mm). Similarly, for S2, highest irrigation amounts were recommended by CB method (69 mm) which was again almost 44% greater than that of EPIC treatment (48 mm). Although no significant difference in corn grain yield was observed, the study suggests that highest irrigation amounts do not always result in maximum yield.

2.5 Conclusions

The results of this study suggest that it is possible to substantially reduce the amount of irrigation water applied by altering the irrigation scheduling method without significantly impacting corn yield. The online ET based irrigation management assistant (IMA) tool recommended the lowest amount of irrigation as compared to other methods without impacting the crop yield significantly. Though the corn seasonal ETc was reduced significantly as compared to other treatments under IMA method, the impact of this reduction in ET was not significant on the grain yield. For one of the site years – Y1S2, both SM and IMA method had lower crop evapotranspiration but no significant difference in corn yield was observed. Maximum PWU was observed for EPIC method in Y1 and for IMA based irrigation scheduling in Y2 at both sites. Both IMA and EPIC methods resulted in significantly higher PWU on average for all site-years of the study.

In all years and sites no significant differences were observed in measured N uptake between irrigation treatments. This might suggest that ETc was not limited by water application and all irrigation treatments recommended enough irrigation to maintain the ETc required for crop production. Though not significant, a positive relationship between PWU and N uptake was observed for three site years except Y1S2. Irrigation scheduling methods were observed to significantly impact NO_3-N leaching at two site years of the study Y1S2 and Y2S2. The CB method and IMA method of irrigation scheduling resulted in significantly higher and lower cumulative nitrate leaching respectively on average for all site years of the study. This is because CB method had significantly higher water losses and IMA method had lowest irrigation recommendations. Although both SM and CB method resulted in higher irrigation amounts, however due to differences in timing of irrigation maximum nitrate loss was observed in the CB method. Precipitation was also observed as a major factor influencing nitrate leaching, the precipitation at S1 decreased from 632 mm in Y1 to 402 mm in Y2 which resulted in an 83% overall reduction in the total nitrate leaching.

In this study no significant difference in corn grain yield was observed among irrigation scheduling treatments for all site years. The EPIC method based irrigation scheduling resulted in highest yield for Y1 at both sites and this was not the method that received highest irrigation. Smaller and more frequent irrigation in case of EPIC method may have resulted in higher yields. In the second year of the study one of the higher irrigation methods – CB method, resulted in higher yields at both sites. In general, treatments with lower irrigation rates exhibited the highest IWUE and vice-versa in all seasons and sites.

Chapter 3

Development of irrigation trigger points and comparison of soil moisture sensors

3.1 Overview

Rapid adoption of supplemental irrigation in agriculture coupled with lack of knowledge and tools necessary for sustainable irrigation management has agronomic as well as environmental concerns especially for coarse textured soils. While insufficient irrigation induces crop water stress and impacts crop yield, excess irrigation wastes water, increases water procurement costs, and has the potential to cause nutrient pollution in ground and surface water bodies. Soil moisture monitoring is one of the techniques used for effective irrigation management. Major challenges in the use of soil moisture sensors are sensor inaccuracy and lack of soil specific calibration.

In this study, the performance of the Irrometer 200SS Watermark granular matrix sensors, Vegetronix VH400 sensors and Acclima TDR 315L sensors is compared against neutron probe for sensor accuracy in predicting soil volumetric water content. The study was conducted at two sites in Central Minnesota – Sand Plain Research Farm, Becker, MN and Rosholt farm, Westport, MN for the two corn growing seasons – 2019 and 2020. A soil water retention curve (SWRC) is the relationship between amount of water present in the soil and it's matric potential. Site-specific SWRCs for watermark sensors were obtained from watermark sensor measured soil matric potential data and measured neutron probe volumetric water contents. Also, Irrigation Trigger Points (ITP) were developed for watermark sensors for coarse textured soils at both sites – Hubbard-Mosford complex (sandy, mixed, frigid, Entic Hapludoll) and Arvilla sandy loam (sandy, mixed, frigid, Calcic Hapludoll).

High R^2 values (0.74, 0.64, 0.72, 0.72, 0.70, and 0.52) for SWRCs obtained from soil matric potential measured by watermark sensor ($\Psi_{m\text{-}WM}$) and volumetric water content measured by neutron probe ($\theta_{v\text{-}NP}$) at both sites and at all three depths (0.3, 0.6 and 0.9 m) suggest good correlation between $\Psi_{m\text{-}WM}$ and $\theta_{v\text{-}NP}$. Site-specific SWRCs developed from measured $\theta_{v\text{-}NP}$ and $\Psi_{m\text{-}WM}$ data consistently performed better than general SWRCs based on soil textural class (SSURGO) at both sites. Watermark sensors performed best in comparison to neutron probe, with lowest RMSD and highest R^2 value, followed by Acclima TDR sensors. However better performance of watermark sensors may be attributed to site and depth specific calibration.

3.2 Introduction

Currently, Minnesota has approximately 2.5 lakh hectares of irrigated agricultural cropland, a number that increased by 4% from 2007 to 2012 (USDA NASS, 2012). Since irrigation has been adopted so rapidly in the state, farmers lack the knowledge, experience and tools necessary for sustainable irrigation management. According to the 2013 Farm and Ranch Irrigation Survey, 89% of Minnesota farmers use 'condition of the crop' method to decide when to irrigate (Vilsack & Reilly, 2014). This method of irrigation scheduling could lead to over-irrigating and many times under irrigating the crop. While, insufficient irrigation induces crop water stress, diminish crop yield, and lower economic returns, over-irrigation at the same time wastes water, increases pumping cost and negatively impacts the environment by degrading surface and groundwater quality through chemical or nutrient pollution (Payero et al., 2017). In Minnesota, since most of the irrigated acres are in the central sands region of the state, two critical problems are associated with improper irrigation – water quality and quantity. Water percolates through the soil profile quickly in the coarse-textured soils of central Minnesota. Along with percolating water, some important nutrients for crop production, often supplied through fertilization can leach quickly through the root zone and into groundwater. Fertilizer loss represents a financial loss to the farmer as nutrients are leached beyond the root zone. Further, fertilizer leaching poses environmental, human health, and economic risks to communities that use groundwater for drinking. Many irrigated regions of the state have groundwater with nitrate-nitrogen concentrations exceeding the 10mg/L health standard for drinking water. In addition, high groundwater withdrawals during the crop growing season can temporarily reduce the discharge of groundwater into nearby streams and lakes, impacting aquatic ecosystems (MN DNR, 2016; Watson et al., 2014) as well as causing interference with nearby private and municipal wells.

A meaningful way to address these issues is by implementing better irrigation management techniques and technologies. Irrigation scheduling enables the irrigator to apply the right amount of water at the right time, which increases irrigation efficiency and reduces nitrate-N leaching. Irrigation management using soil moisture sensors is considered one of the best methods of irrigation scheduling in term of reducing water use while maintaining higher crop yields and profits (Steele et al., 1994). For example, in a study conducted in Florida, a 15% to 51% decrease in irrigation water and 11% to 26% increase in crop yield was observed by users who manage irrigation with soil moisture sensors compared to fixed-time irrigation plan (Zotarelli et al., 2009). With the advent of Internet of Things (IoT) and other information technologies in soil moisture sensing industry, soil moisture sensors have diversified and evolved substantially over the past decades. As a result, there is a multitude of options available for farmers, farm managers or other stakeholders to invest in sensor-based irrigation decision making. However, because of the wide range of sensors available in the market, farmers find it difficult to make a decision as to which sensor is best for their soil type and how to interpret the data collected using these sensors, limiting the adoption of these soil moisture measuring devices.

A variety soil moisture sensors exist commercially utilizing different sensing technologies such as neutron scattering, Time Domain Reflectometry (TDR), electric resistance, Frequency Domain Reflectometry (FDR) or capacitance etc., (Suat Irmak et al., 2014; Leib et al., 2003; Payero et al., 2017; K. Sharma et al., 2021). The neutron probe method is considered to be the most accurate method of measuring soil moisture. Neutron probes consist of a neutron source, detector, and an electronic counting scale. This radioactive probe emits high-energy neutrons (Americium 241/Beryllium) in all directions into the soil. When these neutrons collide with hydrogen atoms in the soil, the speed of the neutron is attenuated or slowed down. The rate of attenuation is dependent on the amount of water present. The TDR and FDR or the capacitance sensors works on the principle of dielectric constant of different components in the soil (air, water and solids). The TDR sensors consist of two or three parallel rods inserted into the soil acting as waveguides. When a defined voltage pulse is sent to the sensor it travels along the waveguide. When this pulse reaches the end of the waveguide it reflects back. As the soil moisture increases, the dielectric constant of the soil increases. Consequently, the travel time of the pulse decreases and thus, the soil moisture content can be estimated using the calibration equation (Topp et al., 1980). The FDR or capacitance sensors are typically in the form of two parallel rods (two electrodes) or a pair of metal rings mounted along the length of PVC. When an oscillating frequency is applied to the electrodes, the soil around the electrodes (or around the tube) forms the dielectric of the capacitor that completes the oscillating circuit. The changes in soil moisture can be detected by changes in the operating frequency. The electric resistance sensors operate on the principle that water conducts electricity and dry soils do not. These sensors usually consist of two electrodes enclosed in a porous material. When the sensor is in good contact with the surrounding soil, the water suction in the porous material comes in equilibrium with the soil water suction. With the change in soil water, the water content in the porous material also changes which affects the electrical resistance between the two electrodes. For instance, if the water content decreases, the electrical resistance between the electrodes increases, which can be measured from the changes in the voltage output when electric current is applied to the one of the electrodes. Using a calibration equation this voltage output can be converted into matric potential.

These soil moisture monitoring systems can be single probes with multiple sensors at different depths while others are point-based single sensors. These sensors can also be portable (use same sensor for different location by installing access tubes) as well as in-situ sensors. Some of these moisture sensors can be manually operated which involves manually taking readings periodically, while some can take continuous measurements involving automatic monitoring and telemetry. Each of these sensors has its advantages and drawback in terms of cost, accuracy and reliability. While neutron probe sensing technology is one of the most reliable and accurate for determining soil water content, due to its radioactive source, high maintenance requirements and high cost, its use has been seen mostly limited to research purposes. On the other hand, major developments and adoption of capacitance sensors, TDR sensors and resistance sensors have been seen in recent years. However, some of these sensors are sensitive to temperature, clay content in the soil and high salt concentrations. In addition, sensors readings are affected by site characteristics such as soil type and moisture, soil homogeneity, and the presence of stones and roots (Mittelbach et al., 2012). All sensor manufacturers have generic equations for different soils, however, when a soil-specific calibration is performed, the performance of a given sensor can be increased (Vaz et al., 2013). Therefore, it is essential to evaluate the performance of different soil moisture sensors based on site-specific calibration equations for agricultural fields. Since it is a time consuming and difficult process, most farmers do not like to perform the on-site sensor calibration. Thus there is a need that researchers, extension specialists and industry personal to help develop the local guidelines for different sensor use and performance as well as guidelines for data interpretation. In recent years, extensive research has been conducted both in field and lab settings to understand the performance of different soil moistures sensors in different soil types.

The goal of this research was to provide farmers, a better understanding of the accuracy of different sensors and calibration curves that they can use for irrigation scheduling. This study has two specific goals: firstly, our study investigated the performance of three soil moisture sensors, namely Irrometer Watermark 200SS, Acclima TDR 315L and Vegetronix VH400 by comparing it with standard neutron probe soil moisture sensor in two common soil types in irrigated region of Minnesota. Secondly, we are focused on providing an easy to use and affordable irrigation management option to farmers. Therefore this study aims at developing irrigation trigger points for Irrometer Watermark Sensors for two soil types in MN to enable farmers in the area to use research-based, convenient, and affordable irrigation decision making.

3.3 Materials and Methods

3.3.1 Site and soil type description

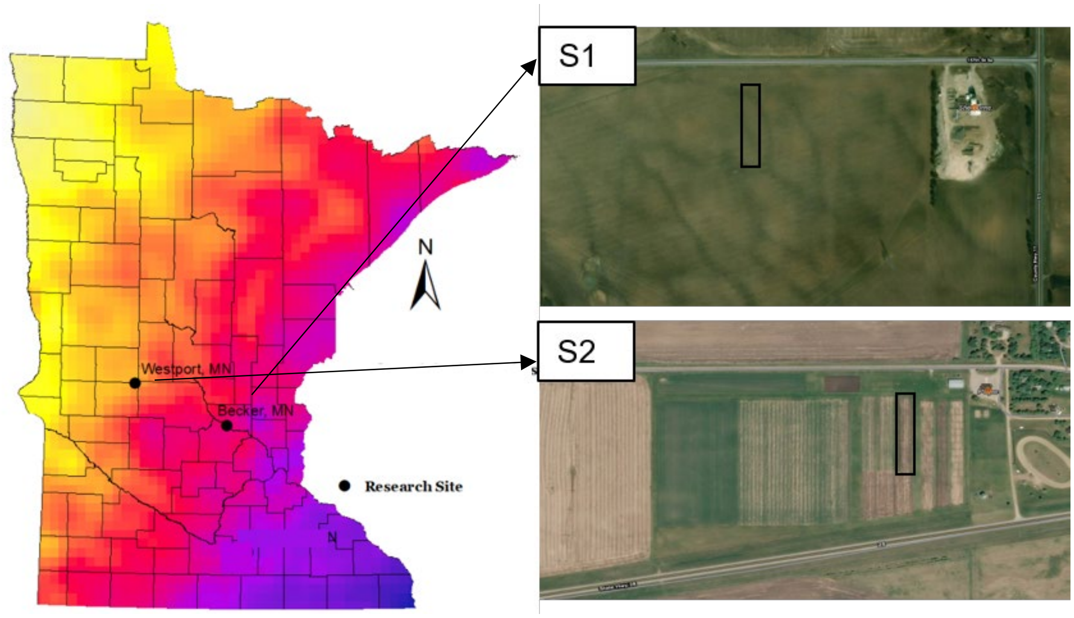

Figure 3.1. Geographic location and visual depiction of experimental sites S1 and S2 in central Minnesota

Field trials were conducted during 2019 and 2020 corn growing seasons at two research sites in Minnesota that represent two highly irrigated regions of the state. Site 1 (S1) is the Sand Plain Research Farm (SPRF) in Becker, Minnesota (45°23'N 93°53'W) and site 2 (S2) is the Rosholt Research Farm in Westport, Minnesota (45°42'N 95°10'W). Irrigated row crop, field maize (*Zea mays* L.) was grown in 2019 and 2020 growing seasons at both sites. Since the sites are situated in Central Minnesota and have coarse textured soils with low available water storage. Therefore, the soils in the region cannot consistently store enough water for crop uptake, making irrigation critical to prevent crop water stress.

The soil at S1 is Hubbard-Morford complex (sandy, mixed, frigid, Entic Hapludoll) which is a glacial outwash soil and has a sandy alluvium parent material with 0-3 % slopes. In the top 120 cm of soil, this soil has bulk density of 1.66 g/cm^3, organic matter content of 0.79 %, field capacity volumetric water content of 12.0% and permanent wilting point of 4.2 % (Web Soil Survey NRCS USDA, 2021). The soil at S2 is Arvilla sandy loam (sandy, mixed, frigid, Calcic Hapludoll) with loamy glaciofluvial deposits over sandy and gravelly outwash parent material with 0-2% slopes. In the top 120 cm of soil, this soil has bulk density of 1.61 g/cm^3, organic matter content of 0.72 %, field capacity volumetric water content of 12.7 % and permanent wilting point of 5.8 % (Web Soil Survey NRCS USDA, 2021). Although these soils have higher organic matter content at shallow depths – 2.03% and 1.23 % at 0-30 cm and 0-60 cm respectively. Tables 3.1 and 3.2 show the soil texture classification percentage and available water storage for both the sites. Both sites had high sand percentage, and hence low available water. The top 120 cm of soil have less than 10 cm of available water.

The plots were in a continuous corn cropping system at both locations. Chisel plow was used to till the soil to a depth of 15-20 cm at S1. For S2, Orthman strip till equipment was used as strip till combines the benefits of chisel plowing and no-till for row crops. The individual plot size was 12.19 m x 18.29 m at S1and 7.62 m x 15.24 m at S2. The number of rows planted with corn crop in each plot were 16 and 10 for S1 and S2 plots respectively. Total growing season precipitation in Y1 growing season was 632 mm and 538 mm for S1 and S2 respectively. For growing season Y1 total seasonal precipitation was 402 mm and 457 mm for S1 and S2 respectively.

Table 3.1. Particle distribution in top 120 cm of soil at sites S1 and S2

Particle	S1	S2
Sand (%)	87.9	80
Silt (%)	8	12.3
Clay (%)	4.1	7.7

(Web Soil Survey, NRCS, USDA)

Table 3.2. Available water storage in top 120 cm of soil at sites S1 and S2

Soil Depth (cm)	AWS (cm) S1	AWS (cm) S2
0-30	3.4	4
30-60	2.67	2.78
60-90	2.04	0.99
90-120	1.59	0.96
0-120	9.71	8.74

(Web Soil Survey, NRCS, USDA)

3.3.2 Sensors description and installation

Four different commercial sensors were compared in this study namely InstroTek 503 ELITE Hydroprobe, Irrometer Watermark Granular Matrix Sensor, Vegetronix VH400 and Acclima TDR Sensor. Watermark sensors were installed at depths of 0.15, 0.3, 0.6 and 0.9 m at 8 and 7 locations at S1 and S2 respectively in first year of the study Y1. In Y2, the sensor installation depth remained the same but as some damage was observed to two of those units, 6 and 7 units (each having 4 sensors at 0.15, 0.3, 0.6 and 0.9 m depth) were installed at S1 and S2 respectively.

Hence a total of 15 units (each having 4 sensors) or 60 watermark sensors were installed in Y1 and in Y2, 13 units or 52 sensors were installed in total at both sites.

The Vegetronix VH400 sensors were only installed in the second year of the study at both sites. At S1, they were installed at depths of 0.3, 0.6 and 0.9 m and at S2 due to presence of gravel below 0.75 m they were installed at depths of 0.3, 0.45 and 0.6 m. A total of 16 units with each having 3 sensors at the above mentioned depths were installed at both sites. 8 units or 24 sensors were installed at S1 and 8 units or 24 units were installed at S2.

The Acclima TDR sensors were installed at a single location (S1) for both years of the study because of their high cost. A total of 4 sensors were installed two of them were installed at 0.3 m depth and the other 2 at 0.6 m depth. The neutron probe access tubes were installed at 12 locations in all four site years of the study and soil water content measurements were taken at depths of 0.3, 0.6, 0.9 and 1.2 m at S1 and at depths of 0.15, 0.3, 0,45, 0.6 and 0.75 m at S2.

All the sensors were installed according to manufacturer's recommendations and default or factory calibration was used (except for the neutron probe) to obtain results similar to what irrigator/ farm manager would obtain in the field. Also, all of the sensors – watermark, Vegetronix, and TDR sensors and neutron probe access tubes were installed in close proximity (0.3 – 0.6 m) to each other in crop row such that soil water contents measured at same depth and same location are comparable to each other. The sensors used in the study are described below in terms of their principle of working, construction, installation depth and measured parameter.

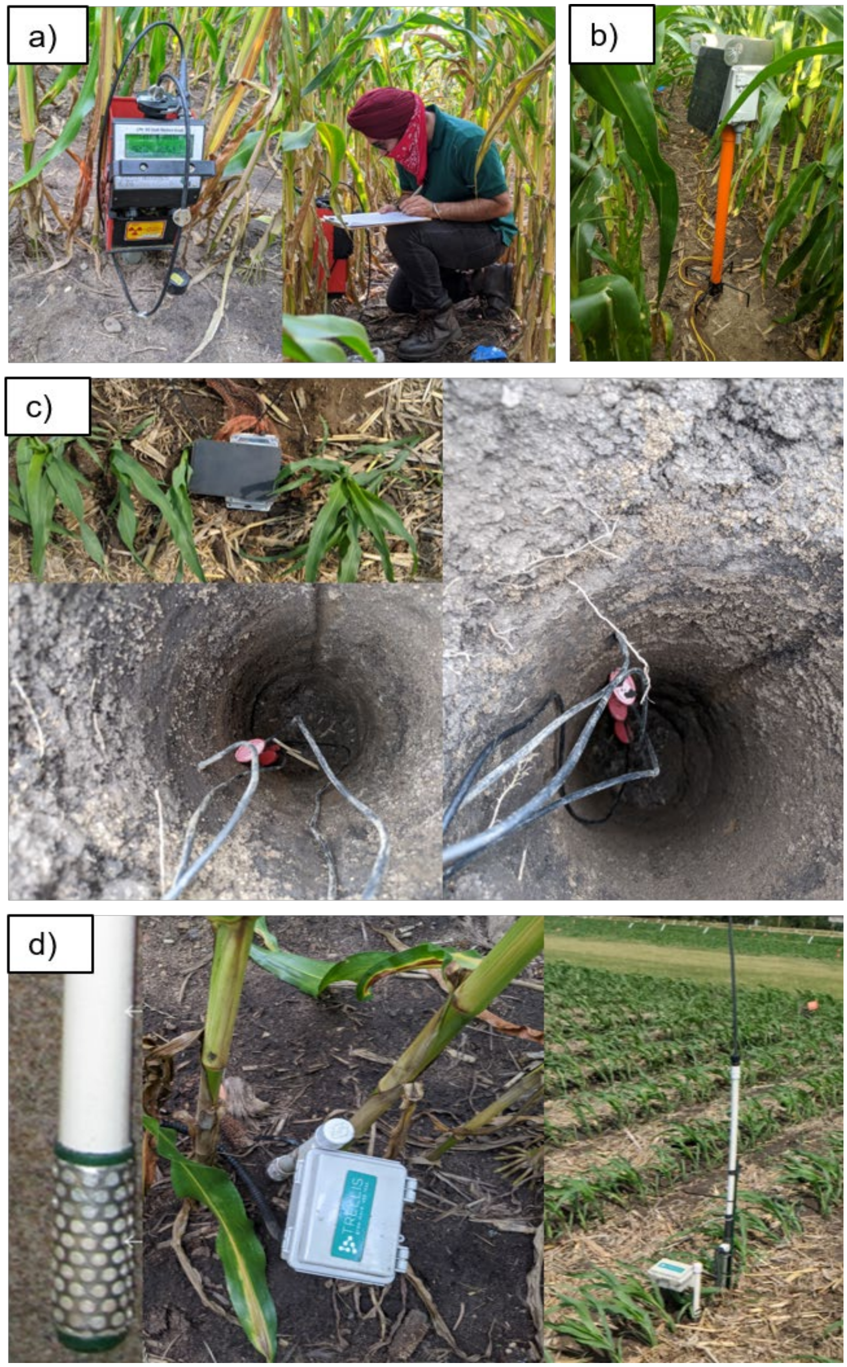

Figure 3.2. Visual depiction of soil moisture sensors and associated telemetry units at both sites (a) Neutron probe (b) Acclima TDR (c) Vegetronix VH400 (d) Watermark Sensor

a. Neutron probe

A neutron probe is a sophisticated equipment that measures the moisture content in soil and requires operation by a licensed operator. The neutron probe comprises of a nuclear unit, suspended on a cable, which is both a neutron source and detector, a housing containing the electronic receptors and a shield for safe transportation of the radioactive device. The nuclear unit is lowered down a metal access tube at predetermined depth intervals. The neutron source starts scattering fast neutrons, which are deflected by hydrogen, most commonly water, and are slowed. The source also detects and counts these returning slow neutrons. The amount of deflection is directly related to the soil moisture in the soil. In this study neutron moisture meter, InstroTek 503 ELITE Hydroprobe, was used to conduct weekly measurements of volumetric water content of soil. Further, volumetric water content was used to calculate the soil water deficit in root-zone of crop. At the beginning of the growing season, metal access tubes were installed in the middle of center rows of each plot up to 1.2 m deep with a rubber stopper fixed at the bottom to prevent any water movement from below the soil. The above ground part of those access tubes was always covered with a cap to prevent any water from precipitation or irrigation events from going into the tubes. Before taking the measurements, standard count of neutron probe was taken, and it was made sure that the probe passes the test. The center of the Neutron probe bottom was placed on top of the access tube in a way that the hole below the probe coincides with the tube and fits onto it. The neutron emitter was then lowered into the tube to take four volumetric water measurements at intervals of 0.3 m depth over a total depth of 1.2 m at Site 1. At S2 five measurements were taken at an interval of 0.15 m up to a depth of 0.75 m due to presence of gravel below 0.75 m at S2.

b. Watermark sensor

Watermark Granular Matrix Sensor (Irrometer Co., Riverside, California) is an electrical resistance type sensor. The principal of operation of this sensor is based upon electrical resistance and the fact that water conducts electricity and dry soil does not. A stainless-steel casing with holes is used to protect the sensor. The sensor has two electrodes enclosed in a block of porous material (usually gypsum). As the environment or surrounding water content change on the outside of sensor similar change occurs inside the sensor and the suction inside the porous block attains equilibrium with suction of surrounding soil. Any change in the water content inside the sensor changes the resistance between those electrodes'. As the amount of water between electrodes increases the resistance between them decreases. This change in electrical resistance can be obtained in terms of matric potential of soil water, which can later be converted to volumetric soil water content using soil moisture retention curves. Although total soil moisture potential is the sum of gravitational, osmotic, and matric (or pressure) potentials, generally gravitational and osmotic potentials are not taken into account when referring to soil moisture potential. So, soil water potential simply refers to the matric potential of soil water as far as the scope of this study is concerned. In this study four sensors were vertically connected with each other using PVC pipes to form one unit. These units were installed in the soil such that the sensors are at 0.15, 0.3, 0.6, and 0.9 meters depth below the soil surface to capture soil moisture values in the root zone of the soil. The soil water potential measurements were taken at intervals of two hours approximately. The sensors from different soil depths at a particular location are connected to the watermark circuit board inside the telemetry unit or panel box (Fig 3.2 d). All these telemetry units were connected to a central base station outside the field through a wireless antenna connection. Soil moisture data from all the watermark sensors connected to telemetry unit and further to central base station was obtained from the online Trellis Dashboard which can be accessed through internet browser or Trellis mobile application.

c. Vegetronix VH400 sensor

The VH400 Vegetronix Sensors (Vegetronix Inc., Utah) are small soil moisture measurement sensors with very thin blades externally labelled similar to a measuring ruler as shown in Figure 3.3 c. The sensors measure the dielectric constant of soil through an internal voltage regulator with input voltage ranging from 3.5 to 20 volts (VDC). The required input current should be less than 7 mA and the output voltage produced is between 0-3 volts (VDC) which can be measured using a multimeter, a data logger or a microcontroller. The voltage output can be interpreted as volumetric water content of soil after processing it through Voltage – VWC curves provided on the sensor website. The temperature range in which these sensors can work is from -40 to +85 degrees Celsius. This is a low cost sensor that measures dielectric constant of soil almost instantaneously within a very short time – a measurement time of 400 milliseconds is needed for a stable output. Vegetronix claims the sensors to work well in saline soils as well because it uses transmission line technique as in the case of TDR sensor to measure soil moisture regardless of soil salinity. In this study, three soil moisture sensors were connected to sensor nodes to obtain soil moisture data at three depths (0.3, 0.6, 0.9 meters) to monitor soil moisture levels in the crop root zone. The sensor nodes included a solar panel, battery unit, SD card, a charge control unit, data logger unit and three soil moisture interface units connected to soil moisture sensors at three depths. The sensor nodes were assembled as per instructions received from GEMS (Genetics Environment Management Socioeconomics) IoT team at University of Minnesota. The data collected by Vegetronix sensors were also remotely accessed through GEMS IoT data loggers.

d. Acclima TDR sensor

In this study Acclima True TDR-315L Sensor (SDI-12) sensors were used. The TDR sensor is based on the principle of Time Domain Reflectometry (TDR) which measures volumetric soil moisture content based on the travel time of an electromagnetic pulse transmitted across parallel probes inserted in the soil at a certain depth. The pulse travels slowly in wet soil due to higher dielectric constant (K) of wet soil and faster in dry soil due to lower dielectric constant (K) of dry soil. Hence, soil water content values can be obtained at desired depths very rapidly. A study conducted by Topp et al. (1980) confirmed that TDR sensing is suitable for volumetric water content in various soil types (Topp et al., 1980) although these sensors are not intended for soils with high clay content. These sensors can be connected to any SDI-12 data logger for collecting instantaneous data. In this study four TDR sensors (waveguides or probes) were connected to EarthScout L200 data logger to form a single unit and the sensors were installed in soil at 0.3 and 0.6 meters depth to obtain soil moisture contents in the root zone of the crop. A total of four sensors were installed for year Y1 and Y2 (2019 and 2020) of study at site S1, two of them being at 0.3 meters depth and another two at 0.6 meters depth. The soil moisture data was accessed through the EarthScout online portal.

3.3.3 Soil water retention curves

Soil water status in a field can also be measured through soil water potential. A soil water retention curve is a relationship between soil matric potential and water content that describes the ability of a soil to hold water. This relationship is unique for each soil. As discussed earlier, soil water potential simply refers to the matric potential of soil water in this study. In this study soil matric potential values from watermark sensors are used against volumetric water content of neutron probe in order to develop soil water retention curves such that the output from watermark sensors, which is soil matric potential, can be translated to volumetric water content measurements of a neutron probe.

Monitoring of field water balance is one of the methods that forms the basis of irrigation scheduling. In general, soil matric potential increases with increase in crop water stress and hence decreases with increase in volumetric water content of soil. In most sandy soils, the values of soil matric suction range from 10 to 199 KPa (Suat Irmak et al., 2014). These curves are specific to soil type and also observed to be different for different depths. In this study, SMRCs are developed for two soils - Hubbard-Mosford complex (Loamy sand) at site S1 and Arvilla sandy loam (Sandy loam) the soil at site S2 and at depths of 0.3 m, 0.6 m and 0.9 m.

In addition to development of SWRCs from soil matric potential data from watermark sensors and volumetric water content measurements from neutron probe, soil water retention curves based upon previously developed methods were obtained in order to compare site-specific SWRCs to generalized SWRCs developed in the past based upon soil physical characteristics. One of the SWRCs is based on the van Genuchten (1980) equation based on Mualem pore-size model (Mualem, 1976; van Genuchten, 1980).

$$\theta v = \theta r + (\theta s - \theta r)/ [1+(\alpha \Psi_m)^n]^m \quad (1)$$

In equation (1), θv is soil water content at given soil matric potential or suction Ψ_m (taken as positive), θs and θr represent saturated and residual water content respectively. α, n and m are independent parameters observed from soil water retention data, where m = 1 – 1/n. α, n and θr values are obtained for loamy sand (S1) and sandy loam (S2) soils from another study which reported soil water retention characteristics for a variety of soils (Carsel & Parrish, 1988). Saturated water content θs are obtained from a study which reported saturated water contents based on soil texture and organic matter content (Saxton & Rawls, 2006).

The second equation used in the study was developed by Saxton et al. in 1986 which estimated SWRCs based on readily available soil texture data instead of soil water retention characteristics (Saxton et al., 1986). This is a unique SWRC as according to this equation volumetric water content remains constant and equal to saturation water content (θs) with increase in soil matric potential up to air entry suction (Ψ_e).

For Ψ_m = 0 to Ψ_e KPa, $\theta v = \theta s$;
For $\Psi_m = \Psi_e$ to 10 KPa, $\theta v = \theta r + ((10-\Psi_m) *(\theta s - \theta r))/ (10- \Psi_e)$;
For Ψ_m = 10 to 1500 KPa, $\theta v = (\Psi_m/A)$ ^ $(1/B)$ (2)

In equation (2), Ψ_e refers to air-entry suction and coefficients A and B can be calculated using other set of coefficients mentioned in the study (Saxton et al., 1986). θv is soil water content at given soil matric potential Ψ_m (taken as positive), θs and θr represent saturated and residual water contents respectively.

3.3.4 Development of irrigation trigger points

Irrigation management requires measurement of soil water status from time to time during the crop growing season. Watermark sensors are capable of providing continuous soil matric potential (KPa) data which can be converted into volumetric water content of soil through soil moisture retention curves. For effective irrigation management, these sensors can be installed in representative areas of the field for accurate measurement of soil water status. For optimum crop growth and yield, the soil water needs to be maintained between desired upper and lower limit of available water (the portion of soil water that is available for plant uptake). A soil water retention curve is a relationship between soil matric potential and water content that describes the ability of a soil to hold water. This relationship is unique for each soil. For sandy soils, due to their large pore size water drains easily, hence, the associated irrigation trigger point is close to 30-50 KPa in contrast to silt-loam or clayey soils which have higher irrigation trigger points. The upper limit of available water for the crop is the field capacity of the soil. For sandy soils, it takes about 24 hours for soil to reach field capacity through natural drainage after a heavy rainfall event. The Maximum Allowable Depletion (MAD) is the maximum amount of water that an irrigation manager decides to get depleted before scheduling subsequent irrigation. Conventionally a depletion of about 50% of available water is used as MAD for corn crop but MAD values can be varied to obtain better yields and foster efficient use of water. MAD values should not be exceeded to more than 70% of available water holding capacity to save crop from excessive water stress. The irrigation trigger points are developed based upon measurements taken at 0.3, 0.6 and 0.9 m at both sites respectively.

3.3.5 Field calibration of neutron probe

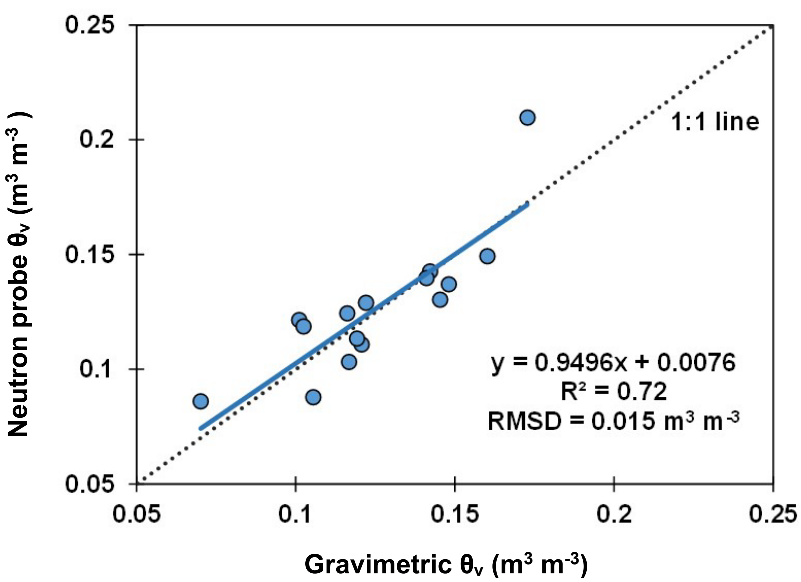

Figure 3.3. Calibration of neutron probe volumetric water content to volumetric water content obtained through gravimetric method at S1

Field calibration of neutron probe was conducted using gravimetric soil sampling method. Soil bulk density was calculated with the help of bulk density soil sampler kit. Soil samples were collected at depth of 0.2 and 0.45 m adjacent to neutron probe access tubes installed in plots at site S1 of the study. Moisture content was calculated on dry weight basis by oven drying soil samples at 105 ℃ until constant weight. Finally, volumetric water content was obtained by multiplying moisture content at dry basis with the ratio of bulk density of soil and water density. Neutron probe measurements were conducted simultaneously also at depths of 0.2 and 0.45 m such that soil moisture measurements are taken at same depth and time by using both neutron probe and gravimetric method for appropriate comparison. The relationship between neutron probe and gravimetric volumetric water content (m^3 m^{-3}) is shown in Fig. 3.3. The neutron probe measured volumetric water content (θ_v) compared very well with the gravimetric volumetric water content (θ_v) and had R^2 and RMSD values of 0.72 and 0.015 m^3 m^{-3}. High R-squared value for the calibration equation suggests high correlation between volumetric water content obtained from gravimetric method and the neutron probe, therefore, neutron probe is used as a standard to compare all other soil moisture sensors deployed in the study.

3.3.6 Statistical analysis

Data were analyzed with RStudio Version 1.2.1335 (2009-2019 RStudio, Inc.). The performance and accuracy of soil moisture sensors based on volumetric water content were evaluated using coefficient of determination (R^2) and root mean square difference (RMSD). A uniform significance level of 95% ($p<0.05$) was used for the analysis and neutron probe volumetric water content was used as standard for all other sensors. Sensor volumetric water content accuracy was assumed to be fair for irrigation management if RMSD with neutron probe readings was less than 0.05 m^3 m^{-3} as in previous studies (Fares et al., 2011; Rudnick et al., 2015). Also, other calibration parameters slope and intercept were compared against unity and zero ($p<0.05$) respectively at 95% significance level.

3.4 Results and Discussion

3.4.1 Weather

Table 3.3. Monthly and growing season average temperature (̊C) for two years (Y1, Y2) at two research sites (S1, S2) in comparison with mean average temperature

Avg. Temp. (̊C)	S1 Mean (2016-2020)	S1 Y1	S1 Y2	S2 Mean (2015-2020)	S2 Y1	S2 Y2
May	14.41	11.89	13.57	13.31	10.96	12.54
Jun	20.46	19.45	21.58	19.57	18.81	20.89
Jul	22.28	22.17	23.09	21.12	21.19	21.99
Aug	20.31	19.70	20.95	19.11	18.26	20.07
Sep	16.55	17.14	14.52	15.67	16.03	13.47
Oct	7.21	6.41	5.18	6.55	5.18	3.73
Growing season avg.	17.84	17.31	17.72	16.59	16.11	16.16

(Data collected from local weather station at research sites S1 and S2)

Table 3.4. Monthly and growing season rainfall (mm) for two years (Y1, Y2) at two research sites (S1, S2) in comparison with mean rainfall

Rainfall (mm)	S1 Mean (2016-2020)	S1 Y1	S1 Y2	S2 Mean (2013-2020)	S2 Y1	S2 Y2
May	84.63	158.24	40.64	87.85	152.40	19.81
Jun	84.48	84.58	99.57	104.78	66.80	71.88
Jul	104.14	105.16	94.74	99.57	105.41	163.83
Aug	110.54	87.12	117.35	95.47	79.76	146.56
Sep	77.57	105.41	25.15	62.07	210.57	22.86
Oct	82.04	101.35	34.54	58.48	74.17	43.94
Growing season total	520.75	632.21	402.08	401.02	538.48	457.20

(Data collected from local weather station at research sites S1 and S2)

Monthly weather parameters, average temperature and rainfall, are presented in Tables 3.3 and 3.4 respectively for all site years of the study. Average rainfall and temperature values were obtained from local weather stations established in 2016 for S1 and 2013 for S2 therefore long-term (30 years) mean values were not presented. For S1, the average monthly temperature in Y1 growing season always remained below mean except for the month of September (Table 3.3). Also, monthly rainfall during the growing season months was higher than the mean value (Table 3.4). Both lower temperature and higher precipitation reduced irrigation requirements of the crop since most of the crop water need is fulfilled by precipitation. In Y2S1, average temperatures for the months of June, July and August remained higher than the mean value and also total precipitation during Y2 was lower than mean precipitation for both sites (Table 3.3 and 3.4). Hence, a greater amount of irrigation 140.53 mm (average for all treatments) was applied in Y2 as compared to that of Y1 (101.66 mm) at S1.

For S2, the average growing season mean air temperature (2015-2020) was 16.59 °C and average growing season precipitation (2013-2020) was 401.02 mm. Both Y1 and Y2 growing seasons had higher than average precipitation which amounts to 538.48 mm and 457.20 mm respectively. Hence, lower supplemental irrigation of 32.30 mm and 87.87 mm (average for all treatments) was applied during Y1 and Y2, respectively. Also, for S2, the mean air temperatures for both Y1 (16.11 °C) and Y2 (16.16 °C) growing seasons were slightly lower than the average value (16.59 °C). The irrigation requirement for Y2 were higher than that of Y1 because Y2 monthly average temperatures were higher than mean value in the months of June, July and August in which correspond to higher crop water use and supplemental irrigation was required in these months. Weather variables including precipitation and temperature along with irrigation influence soil water contents for soil at S1 and S2. The neutron probe measured volumetric water content (%) at

S1 remained between 6 % and 21 % and at S2 between 2 % and 24 %. The weather data was obtained from weather stations situated at respective field sites.

3.4.2 Soil water retention curves (SWRCs) using watermark sensors

Soil water retention curves (SWRCs) developed from watermark soil matric potential ($\Psi_{m\text{-}WM}$) and neutron probe volumetric water content ($\theta_{v\text{-}NP}$) measured during two corn growing seasons Y1 and Y2 at sites S1 and S2 at 0.3, 0.6 and 0.9 meters are presented in Figure 3.4. Second-order polynomial regression equations were found to be the best fit for both sites and all three depths at 95% significance level ($p<0.05$) and a decrease in soil water content was observed with increase in soil water matric suction. Due to coarse texture of soils in both sites and low available water holding capacity, neutron probe measured soil water levels remained below 25% for all sites and depths. Also, this study was conducted in parallel with an irrigation management study and due to frequent irrigation (and precipitation) events, soil water levels rarely dropped too low (< 5%). Therefore, a large number of points fall within range of 10-25% volumetric water content measured by the neutron probe. Similarly, most of the soil matric suction values fall within range of 0-50 KPa as obtained by watermark sensors. These are also the typical irrigation range for the soil and the study sites. All six soil water retention curves had high R-squared values – 0.74, 0.64, 0.72, 0.72, 0.70, 0.52, presented in Figures 3.4 a, b, c, d, e, f respectively. High R-squared values suggested good correlation between soil matric potential obtained from watermark sensor and volumetric water content measured by neutron probe at both sites and all three depths (0.3, 0.6 and 0.9 m). Field capacity of soils decreases with depth, consequently, a decrease in soil water content with depth was observed at both sites.

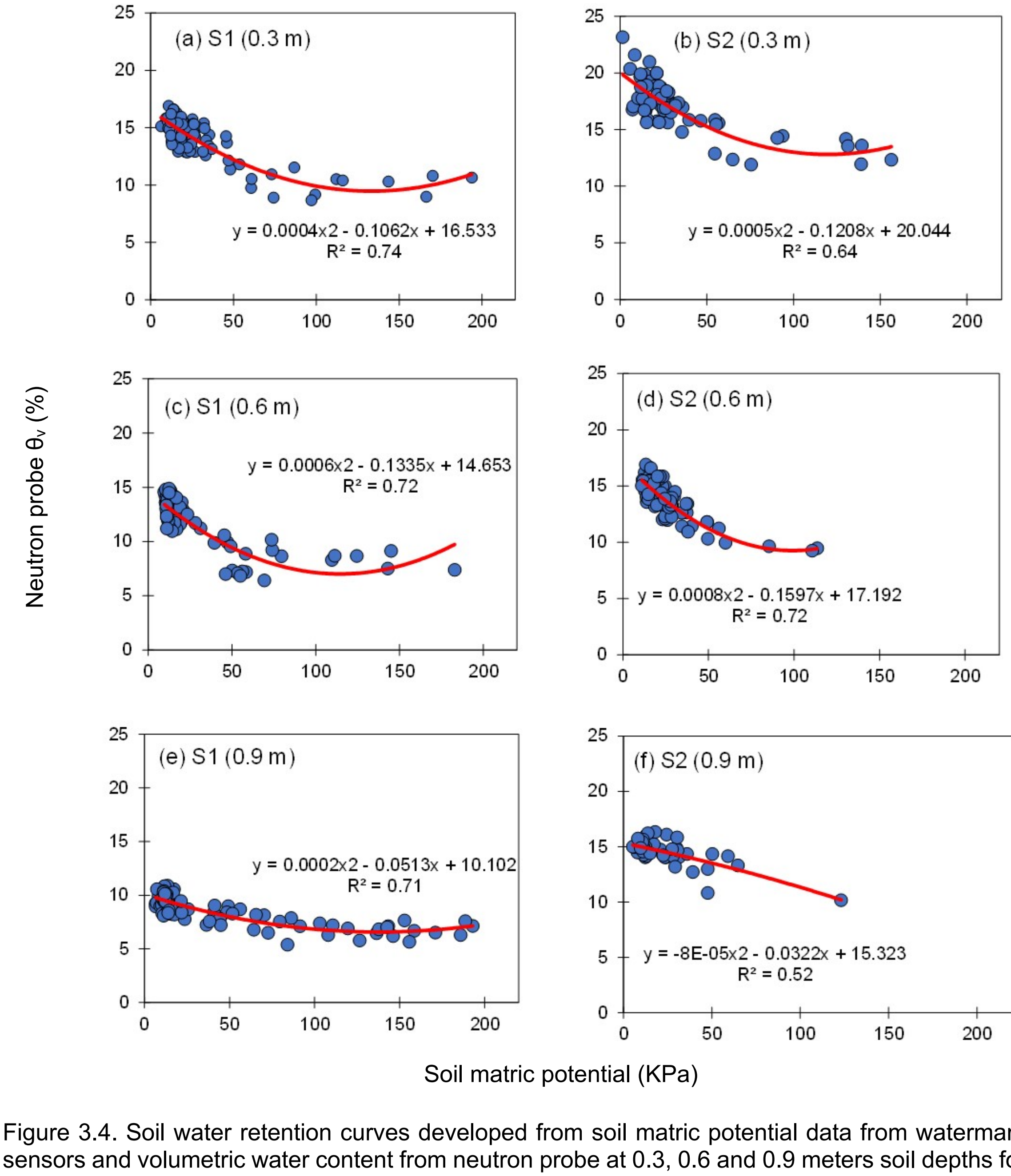

Figure 3.4. Soil water retention curves developed from soil matric potential data from watermark sensors and volumetric water content from neutron probe at 0.3, 0.6 and 0.9 meters soil depths for S1 and S2

Site S2 had more volumetric water content (Figure 3.4) as compared to site S1 at all depths, this was mainly due to higher field capacity of Arvilla sandy loam soil at site S2. Also, at S2 precipitation amounts during the growing seasons were higher than mean precipitation and mean air temperatures during growing seasons at S2 were lower than average for the region.

Two of the polynomial fit (second-order polynomial) SWRCs developed from measured $\Psi_{m\text{-}WM}$ and $\theta_{v\text{-}NP}$ data – S1 and S2 at 0.3 m soil depth (Figure 3.4 a and b) were compared to other soil water retention equations which were estimated based on soil textural class in previous studies (Table 3.5). The comparison was undertaken between SWRCs developed from site-specific data and general SWRCs estimated from soil textural class in order to demonstrate potential differences that may exist when translating $\Psi_{m\text{-}WM}$ to $\theta_{v\text{-}NP}$ data between site-developed and general-estimated SWRCs as the performance of watermark sensors fundamentally depends upon the SWRC used to convert soil matric potential into volumetric water content.

Parameters related to soil physical properties at S1 and S2 were incorporated in previously developed (estimated based on soil textural class) equations in order to obtain site-specific equations for 0.3 meters soil depth at each site. The SWRCs referred as V.G. S1 and V.G. S2 in Table 3.1 are developed based on equation (1) the other two SWRCs referred as Saxton S1 and Saxton S2 are developed based on equation (2) mentioned in the previous section for sites S1 and S2, respectively, at 0.3 meters soil depth.

The polynomial fit equations developed from measured soil water content and soil matric potential data from each site were improved substantially relative to the generalized SWRCs equations based on soil physical properties and textural class. Although better performance of site-specific calibration equations can be attributed to narrow range of volumetric water contents measured in the soil at both sites. The study was conducted in 100 % irrigation plots and hence no dry data points (low volumetric water content) were measured. Both soil texture based SWRCs – V.G. (equation 1) and Saxton (equation 2), need dry data points to be fitted, which was not the case in this study. Therefore, these SWRCs resulted in lower accuracy.

Saxton S2 performed least satisfactorily with RMSD value of 0.076 (m^3 m^{-3}) because equation (2) assumes volumetric water content to be constant and equal to water content at saturation (0.4403 m^3 m^{-3}) for soil matric potential values ranging from 0 to Ψ_e, but the volumetric water content reached maximum of only 0.2316 m^3 m^{-3} at S2 (Figure 3.4 (b)). Rudnick et al. also compared SWRCs developed from measured $\Psi_{m\text{-}WM}$ and $\theta_{v\text{-}NP}$ data and general SWRCs estimated based on soil textural classes and found similar results (Rudnick et al., 2015). The polynomial fit equations developed from measured site-specific data performed best with least RMSD values as compared to general equations developed based on soil textural class (Rudnick et al., 2015).

Table 3.5. Equations and root mean square difference (RMSD, $m^3\ m^{-3}$) values for soil water retention curves (SWRCs) relating soil matric potential (Ψ_m, KPa) measured using Irrometer Watermark sensors (taken as a positive) to volumetric water content (θv, $m^3\ m^{-3}$) measured using a neutron probe at a depth of 0.30 m at both sites S1 and S2

SMRC	RMSD ($m^3\ m^{-3}$)	Equation
Polynomial Fit S1 (0.3 m)	0.0097	$\theta v = 3.987E\text{-}06\Psi_m^2 - 01.062E\text{-}03\Psi_m + 0.1653$
V.G. S1 (0.3m)	0.0434	$\theta v = 0.057 + (0.485-0.057)/((1+(0.124*\Psi_m)$ ^2.28)) ^0.561
Saxton S1 (0.3 m)	0.0330	For Ψ_m = 0 to 1.78 KPa, $\theta v = \theta s = 0.3689$; For Ψ_m = 1.78 to 10 KPa, $\theta v = 0.216 + ((10-\Psi_m)*(0.3689-0.216))/(10-1.78)$; For Ψ_m = 10 to 1500 KPa, $\theta v = (\Psi_m/0.00326)$ ^ (1/-5.0236)
Polynomial Fit S2 (0.3 m)	0.0140	$\theta v = 5.046E\text{-}06\Psi_m^2 - 1.208E\text{-}03\Psi_m + 0.2004$
V.G. S2 (0.3 m)	0.0733	$\theta v = 0.065 + (0.409-0.065)/((1+(0.075*\Psi_m)$ ^1.89)) ^0.471
Saxton S2 (0.3 m)	0.0765	For Ψ_m = 0 to 4.1 KPa, $\theta v = \theta s = 0.4403$; For Ψ_m = 4.1 to 10 KPa, $\theta v = 0.283 + ((10-\Psi_m)*(0.4403-0.283))/(10-4.1)$; For Ψ_m = 10 to 1500 KPa, $\theta v = (\Psi_m/0.00977)$ ^ (1/-5.495)

Also, it was observed that SWRCs estimated based on general textural class at S1 (V.G. S1 and Saxton S1) performed better than those at S2 (V.G. S2 and Saxton S2) with RMSD values of 0.0434, 0.0330 and 0.0733, 0.0765 $m^3\ m^{-3}$ respectively (Table 3.5). This might be due to irregular pore geometry or variations in soil texture at S2. The soil at S2 has high organic matter percentage (up to 2%) from 0-0.6 m depth and has gravel and rocks at depth below 0.6 m. Also, at S2 an older neutron probe Troxler 4302 was used to take measurements for some part of the study which might have caused inconsistency in soil volumetric water content obtained from the study.

A farm manager's ability to predict soil water content from watermark sensors and schedule irrigation is dependent on the SWRC used. For instance, at S2, SWRC developed from measured $\theta_{v\text{-}NP}$ and $\Psi_{m\text{-}WM}$ data (Polynomial Fit S2, Table 3.5) has RMSD value of 0.014 $m^3\ m^{-3}$ which corresponds to about 11% of available water holding capacity (0.13 $m^3\ m^{-3}$) of the soil at S2. On the contrary, a SWRC based on generalized estimation on soil textural class (V.G. S2, Table 3.5) has RMSD value of 0.073 $m^3\ m^{-3}$ and corresponds to about 56% of AWHC of soil. Therefore, site-specific SWRCs developed from measured $\theta_{v\text{-}NP}$ and $\Psi_{m\text{-}WM}$ data are recommended for the purpose of irrigation scheduling. Previous studies also indicate that the use of watermark sensors with site-specific SWRCs can be incorporated to enhance irrigation management (Varble & Chávez, 2011), while watermark sensors without site-specific calibration may still be used to improve irrigation for a specific soil, however, uncalibrated irrigation trigger points might have many limitations (Leib et al., 2003). In this study, Irrigation Trigger Points (ITPs) developed from measured data for S1 and S2 are presented in the next section that can aid in irrigation decision-making from watermark sensors.

3.4.3 Irrigation trigger points using watermark sensors

Irrigation Trigger Points were derived from measured $\theta_{v\text{-}NP}$ and $\Psi_{m\text{-}WM}$ data. The soil matric potential values (taken as positive) obtained from a watermark sensor were averaged on a daily basis and neutron probe measured volumetric water content on that particular day was assumed to reflect volumetric water content corresponding to the watermark soil matric potential. Depletion in soil water content was obtained using the following formula:

$$\text{Depletion (in/ft)} = (\text{FC (\%)} - \text{VWC (\%)}) \times 0.12 \qquad (3)$$

FC – volumetric water content at field capacity of soil (%)
VWC – neutron probe measured volumetric water content (%)

Table 3.6 shows the soil matric potential (measured by watermark sensors) and corresponding depletion values (up to 70% depletion of available water) for S1 and S2 respectively. Growers can decide MAD values, based on the crop and it's growth stage, at which irrigation can be triggered. Using Table 3.6 soil matric potential values (measured by watermark sensors) corresponding to soil water depletion values can be obtained and irrigation can be scheduled using watermark sensors.

Table 3.6. Depletion (cm/m) in available soil water holding capacity versus soil matric potential; available water holding capacity; and irrigation trigger points for soils at both sites

Soil matric potential (KPa)	S1	S2
	Depletion (cm/m)	Depletion (cm/m)
0	0.00 ± 0.00	0.00 ± 0.00
20	1.77 ± 0.67	2.62 ± 0.55
30	3.41 ± 0.74	3.90 ± 0.61
40	4.35 ± 0.77	4.53 ± 0.53
50	5.07 ± 0.37	5.16 ± 0.37
60	5.31 ± 0.63	5.57 ± 0.32
70	5.99 ± 0.36	7.04 ± 1.90
80	6.78 ± 0.32	7.42 ± 1.97
AWHC	10.00 (cm/m)	11.00 (cm/m)
ITP (at 35% depletion)	30-31 KPa	29-30 KPa

A positive relationship was observed between soil matric suction measured by watermark sensor ($\Psi_{m\text{-}WM}$) and depletion in soil water levels obtained from neutron probe measurements at both sites. This is because the more soil water depletion occurs from the rootzone of the crop, the higher is the suction required by the crop to obtain water and hence higher soil matric potential. The range for ITP at 35% depletion of available water holding capacity were 30-31 KPa and 29-30 KPa respectively for S1 and S2 respectively (Table 3.2). A long term field study conducted by Irmak et al. in Nebraska reported similar ITP values of 30-33 KPa and 25-30 KPa (at 35% depletion) for sandy loam and loamy sand soils respectively (Suat Irmak et al., 2014).

The available water holding capacities of soils at S1 and S2 were 1.2 and 1.32 inch/foot respectively (Web Soil Survey NRCS USDA, 2021). The higher available water holding capacity of soil at S2 may be attributed to higher field capacity (21.3 % at 0-0.3 m) and higher OM content (2.03% at 0-0.3 m) of soil at S2 (Web Soil

Survey NRCS USDA, 2021). Also, prior research by Hudson indicated that an increase in OM content of a soil increases its soil water holding capacity (Hudson, 1994). According to the results of our study, both soils undergo 35% depletion around soil matric potential of 30 KPa although soil at S2 has more available water holding capacity. This may be attributed to presence of sand and gravel particles at 0.6 m at S2 (within the crop rootzone). A study conducted by Saxton and Rawls indicated that both OM content and soil texture influence soil water content (Saxton & Rawls, 2006).

3.4.4 Watermark sensor in comparison with neutron probe

The output from watermark sensors is in the form of soil matric potential (KPa) or soil matric suction (taken as positive) that can be converted to volumetric water content through SWRCs. The SWRCs (Figure 3.4) developed from watermark sensor measured soil matric potential ($\Psi_{m\text{-}WM}$) and neutron probe measured soil volumetric water content ($\theta_{v\text{-}NP}$) data were used to convert soil matric potential measurements from watermark to volumetric water content ($\theta_{v\text{-}WM}$). Figure 3.5 shows the linear relationship between ($\theta_{v\text{-}WM}$) and ($\theta_{v\text{-}NP}$) for S1 and S2 at soil depths of 0.3, 0.6 and 0.9 meters from measurements taken during Y1 and Y2 corn growing seasons. The following calibration equation was used for comparing ($\theta_{v\text{-}WM}$) and ($\theta_{v\text{-}NP}$)

$$\theta_{v\text{-}WM} = \text{slope} \times \theta_{v\text{-}NP} + \text{intercept} \tag{4}$$

Table 3.7 explains the relationships between $\theta_{v\text{-}WM}$ and $\theta_{v\text{-}NP}$ among individual site-depths and pooled depths presented in Figure 3.5. Strong relationships existed between estimated ($\theta_{v\text{-}WM}$) and measured ($\theta_{v\text{-}NP}$) data as high R^2 and low RMSD values were obtained (Table 3.7). Since the RMSD values between estimated (θ_{v-WM}) and measured (θ_{v-NP}) remained far below 0.05 (m^3 m^{-3}) for all site-depths individually and pooled data, watermark sensors exhibited good sensor accuracy in predicting θ_v (Fares et al., 2011). Also, the calibration parameters slope and intercept were not significantly different from unity and zero respectively for all the six site-depths individually and also for pooled data within and across sites ($p<0.05$).

Table 3.7 Performance indicators, including root mean square difference (RMSD), coefficient of determination (R^2), regression coefficients (slope and intercept), test for zero intercept, and test for equality of the regression line for unity (i.e., 1.0) between Irrometer Watermark estimated θv (θ_{v-WM}) using soil water retention curves (Table 3.5) and neutron probe measured θv (θ_{v-NP}) for S1 and S2 at 0.3, 0.6, and 0.90 m soil depths.

Site	Depth	RMSD	Calibration Parameters			p-value	
	(m)	(m^3 m^{-3})	Slope	Intercept	R^2	Intercept = 0	Slope = 1
S1	0.3	0.0098	0.7375	0.0364	0.7406	<0.0001	< 0.0001
	0.6	0.0121	0.7260	0.0326	0.7205	<0.0001	< 0.0001
	0.9	0.0074	0.7064	0.0254	0.7045	<0.0001	< 0.0001
	Pooled	0.0098	0.8847	0.0132	0.8857	<0.0001	< 0.0001
S2	0.3	0.0139	0.6367	0.0612	0.6355	<0.0001	< 0.0001
	0.6	0.0087	0.7257	0.0380	0.7234	<0.0001	< 0.0001
	0.9	0.0074	0.5160	0.0701	0.5160	<0.0001	< 0.0001
	Pooled	0.0103	0.7804	0.0328	0.7850	<0.0001	< 0.0001
S1 & S2	Pooled	0.0100	0.8972	0.0132	0.9004	<0.0001	< 0.0001

At both sites S1 and S2 lowest RMSD values were obtained for deeper depth – 0.9 m which may be due to the fact that upper depths (0.3 m, 0.6 m) (Figure 3.5 a, b, d, e) experience more variation in soil moisture as compared to lower depths which have a relatively stable soil moisture content (Figure 3.5 c, f). Previous research confirms that surface depths experience more variation in soil moisture due to the effect of incoming precipitation, irrigation, evaporative losses and greater root presence as compared to deeper depths (Rudnick & Irmak, 2014a, 2014b).

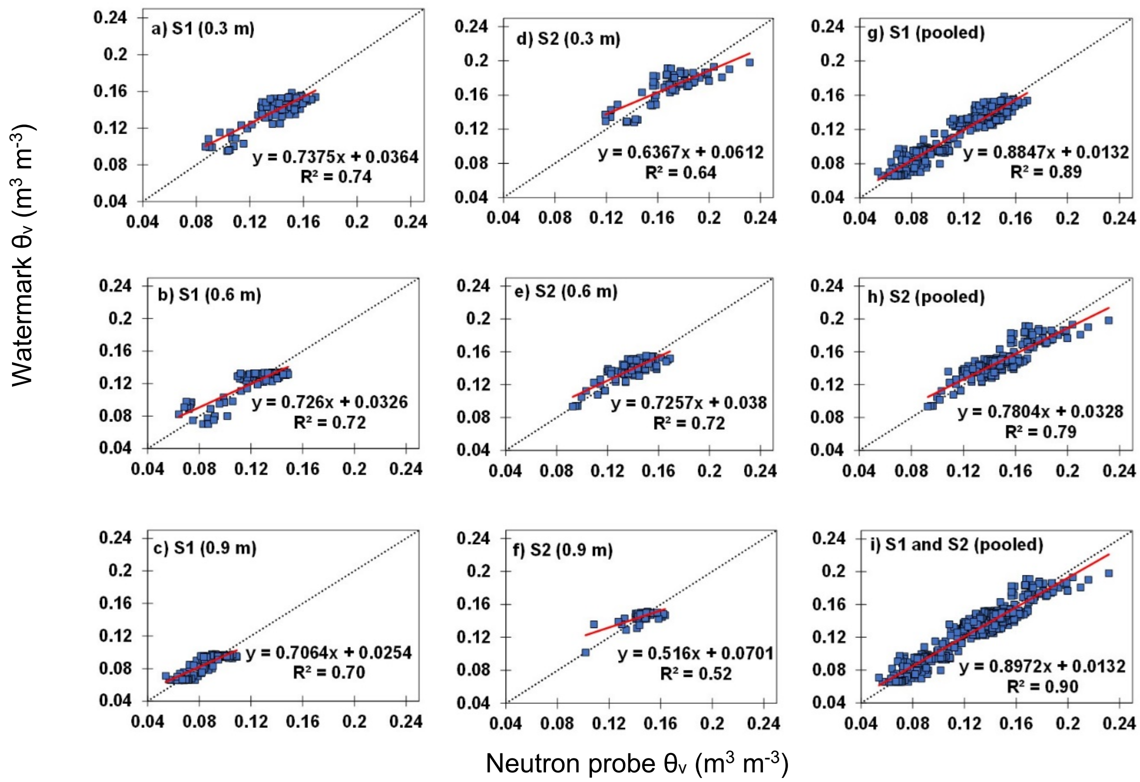

Figure 3.5. Comparison between neutron probe measured and Irrometer watermark estimated θ_v using field calibration equations for 0.3, 0.6 and 0.9 meters soil depths for both sites

Higher R^2 values (0.89, 0.79, 0.90) obtained for pooled data suggest better correlation between pooled $\theta_{v\text{-}WM}$ and $\theta_{v\text{-}NP}$ values for S1, S2 and S1 & S2 combined (Fig 3.5 g, h and i) as compared to individual site-depths (Fig. 3.5 a, b, c, d, e, f). Since $\theta_{v\text{-}WM}$ were calculated from unique SWRCs developed for each site depth individually, $\theta_{v\text{-}WM}$ values were quite accurate and close to measured $\theta_{v\text{-}NP}$ with low RMSE (Table 3.7). Further, an increase in number of data points from individual site-depth data to pooled data resulted in better correlation overall. However, substantial noise in watermark soil matric potential data was observed at both sites and some data points had to be excluded from the analysis which may be due to errors in installation of watermark sensors. Some watermark sensors were observed to report very high soil matric potential readings (usually associated with dry soil) even when soil conditions were wet. The sensors might have lost contact with the soil during dry periods and did not resume contact. Also, some inconsistency in soil moisture data due to use of an older neutron probe was observed.

For all six individual site-depths and pooled depths across sites, the watermark sensor overestimated volumetric water contents for lower soil water levels and underestimated volumetric water content for higher soil water levels as compared to neutron probe (Figure 3.5). There might be a possibility that the soil matric suction inside the watermark sensor was not sufficient to attain full equilibrium with outside soil conditions and therefore could not report higher or lower θ_v values at full extent. There can also be a lag in watermark sensor to adapt to surrounding soil conditions.

3.4.5 Vegetronix VH400 sensor in comparison with neutron probe

Vegetronix VH400 sensors result in an output voltage based on soil water content of soil. The output voltage from the sensor can be converted into volumetric water content of soil using calibration curves. Initially, the output voltage was converted to volumetric water content of soil through the VH400 piecewise calibration curve developed by © Vegetronix Inc. (Vegetronix, 2021) presented in Table 3.8.

Table 3.8. Vegetronix VH400 piecewise calibration curve for obtaining volumetric water content of soil from Vegetronix VH400 sensor output voltage

Voltage range (V)	VWC (%)
0 - 1.1	10*V-1
1.1V - 1.3	25*V- 17.5
1.3 - 1.82	48.08*V- 47.5
1.82 - 2.2	26.32*V- 7.89

When volumetric water contents from VH400 sensor ($\theta_{v\text{-}VH}$) were obtained based on the Vegetronix VH400 piecewise calibration curve (Table 3.8), very high RMSD values of 0.1535, 0.2757 and 0.2356 m^3 m^{-3} (data not presented) were obtained for S1, S2 and pooled S1 and S2 respectively with respect to neutron probe volumetric water content ($\theta_{v\text{-}NP}$) measurements. Alternatively, the output voltage was converted to volumetric water content of soil through the following calibration equation developed by GEMS IoT team (unpublished work) at University of Minnesota, Twin Cities (Schulz, 2021). The equation was developed using METER TEROS sensor as standard at S1 of the study.

$$\theta_{v\text{-}VH} = (V_o * 6.9479) + 4.0051 \quad (5)$$

With the GEMS IoT calibration equation (equation 5), the volumetric water content for VH400 sensors ($\theta_{v\text{-}VH}$) was estimated and then compared to neutron probe measured volumetric water content ($\theta_{v\text{-}NP}$). The adoption of GEMS IoT calibration curve reduced RMSD values to 0.0384, 0.0454 and 0.0431 m^3 m^{-3} for S1, S2 and pooled S1 and S2 data respectively. As better results with lower RMSD values were obtained with the GEMS IoT calibration equation, it was chosen for the purpose of this study.

The following calibration equation was used for comparing ($\theta_{v\text{-}VH}$) and ($\theta_{v\text{-}NP}$)

$$\theta_{v\text{-}VH} = \text{slope} \times \theta_{v\text{-}NP} + \text{intercept} \quad (6)$$

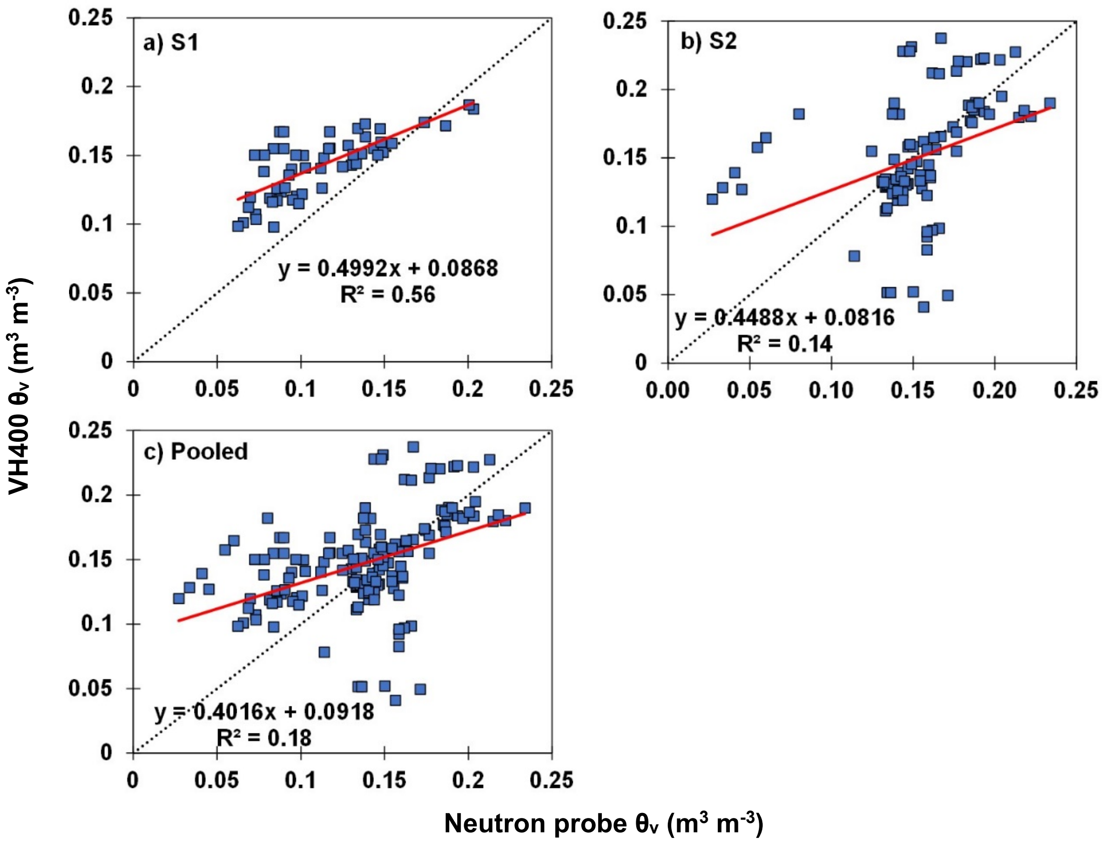

Figure 3.6. Comparison between neutron probe measured and Vegetronix VH400 estimated θv using field calibration equation for both sites S1 and S2

Volumetric water contents from VH400 sensors ($\theta_{v\text{-}VH}$) plotted against volumetric water contents from neutron probe ($\theta_{v\text{-}NP}$) for S1, S2 and pooled data are presented in Figure 3.6. Similar to watermark sensors, VH400 sensors also overestimated volumetric water content at lower soil water levels and underestimated volumetric water content at higher soil water levels (Fig 3.6). Table 3.9 explains the relationship between $\theta_{v\text{-}VH}$ and $\theta_{v\text{-}NP}$ through RMSD and calibration parameters including slope, intercept and R^2 values for measurements taken at S1 and S2 during the Y2 corn growing season at 0.3, 0.6 and 0.9 meters soil depth.

The slopes for $\theta_{v\text{-}VH}$ and $\theta_{v\text{-}NP}$ relationship indicate low performance of the VH400 sensors. For an ideal sensor, slope values should have been close to unity (1) whereas in case of VH400 sensors the slope values are far from unity and even lower than 0.5 (Table 3.9).

Table 3.9. Performance indicators, including root mean square difference (RMSD), coefficient of determination (R^2), regression coefficients (slope and intercept), test for zero intercept, and test for equality of the regression line for unity (i.e., 1.0) between Vegetronix VH400 estimated θv ($\theta_{v\text{-}VH}$) and neutron probe measured θv ($\theta_{v\text{-}NP}$) for S1 and S2

Site	RMSD	Calibration Parameters			p-value	
	($m^3\ m^{-3}$)	Slope	Intercept	R^2	Intercept = 0	Slope = 1
S1	0.0384	0.4992	0.0868	0.5617	<0.0001	< 0.0001
S2	0.0454	0.4487	0.0816	0.1406	<0.0001	< 0.0001
Pooled	0.0431	0.4016	0.0918	0.1820	<0.0001	< 0.0001

Correlation between VH400 estimated ($\theta_{v\text{-}VH}$) and neutron probe measured ($\theta_{v\text{-}NP}$) volumetric water content was higher (R^2 = 0.56) for S1 as compared to S2 (R^2 = 0.14) (Table 3.9). The RMSD value for VH400 sensors at S1 is also lower than that of S2 (Table 3.9). As the $\theta_{v\text{-}VH}$ values were obtained using calibration equation developed at S1 of the study, higher correlation and lower error between $\theta_{v\text{-}VH}$ and $\theta_{v\text{-}NP}$ at S1 was observed due to site-specific calibration of VH400 sensors at S1. A previous study conducted by Vaz et al. (2013) also suggests increase in soil moisture sensor performance with site-specific calibration (Vaz et al., 2013).

The neutron probe measured volumetric water content ($\theta_{v\text{-}NP}$) ranged from 0.0624 to 0.2033 m^3 m^{-3} at S1 and from 0.0271 to 0.2338 m^3 m^{-3} at S2. The range of volumetric water contents measured at S1 was smaller than that of S2. Payero et al. (2017) observed an inverse relationship between range of volumetric water content and % silt (Payero et al., 2017). The results of this study were in contradiction with the previous study since smaller range of volumetric water contents was observed for S1 which also had lower silt % (8 %) than that of S2 (12.3 %).

3.4.6 Acclima TDR sensor in comparison with neutron probe

Acclima TDR sensor measured volumetric water content $\theta_{v\text{-}TDR}$ is compared with neutron probe measured volumetric water content $\theta_{v\text{-}NP}$ in Table 3.10. The output of Acclima TDR sensor is in the form of volumetric water content therefore it was incorporated in the analysis without the use of any calibration equations. The Acclima TDR soil moisture data was collected at S1 of study during Y1 and Y2 corn growing seasons.

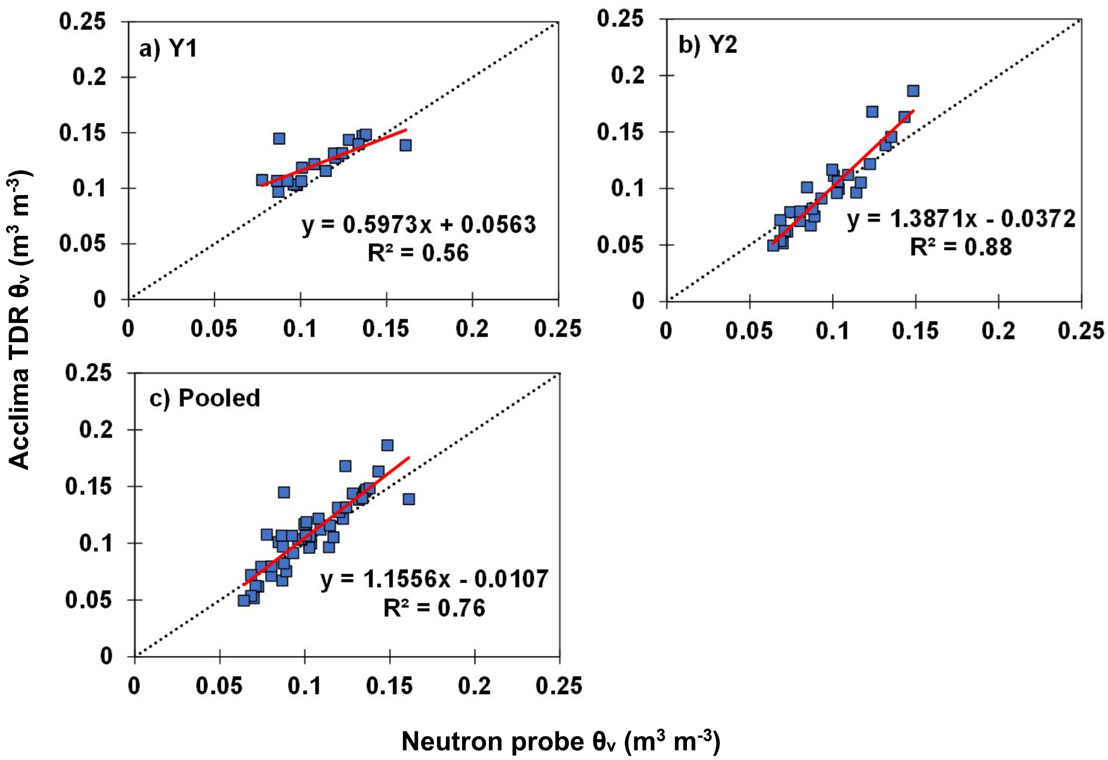

Figure 3.7. Comparison between neutron probe and Acclima TDR measured θv using field calibration equation for both sites S1 and S2

The following calibration equation (7) governs the relationship between $\theta_{v\text{-TDR}}$ and $\theta_{v\text{-NP}}$

$$\theta_{v\text{-TDR}} = \text{slope} \times \theta_{v\text{-NP}} + \text{intercept} \quad (7)$$

Table 3.10. Performance indicators, including root mean square difference (RMSD), coefficient of determination (R^2), regression coefficients (slope and intercept), test for zero intercept, and test for equality of the regression line for unity (i.e., 1.0) between Acclima TDR θv ($\theta_{v\text{-TDR}}$) and neutron probe measured θv ($\theta_{v\text{-NP}}$) for Y1 and Y2

Site	RMSD	Calibration Parameters			p-value	
	($m^3\ m^{-3}$)	Slope	Intercept	R^2	Intercept = 0	Slope = 1
Y1	0.0185	0.6003	0.0560	0.5621	0.0009	0.0001
Y2	0.0156	1.3871	-0.0372	0.8749	0.0014	< 0.0001
Pooled	0.0168	1.1572	-0.0108	0.7559	0.2970	< 0.0001

Volumetric water contents from TDR sensors ($\theta_{v\text{-}TDR}$) plotted against volumetric water contents from neutron probe ($\theta_{v\text{-}NP}$) for Y1, Y2 and pooled data are presented in Figure 3.7. For first year of the study Y1, the TDR sensor also overestimated volumetric water contents at lower soil moisture levels and underestimated volumetric water contents for higher water levels. However, in Y2, the sensors underestimated volumetric water contents at lower soil water levels and vice versa. Similar trends were observed in pooled data. Low RMSD values (<0.05) between $\theta_{v\text{-}TDR}$ and $\theta_{v\text{-}NP}$ for both Y1 and Y2 individually and pooled data suggest high accuracy of the Acclima TDR sensor (Fares et al., 2011). In a recent study conducted by Sharma et al. soil moisture sensors were compared based upon technological principle involved, TDR sensors performed best followed by capacitance and electrical resistance type soil moistures sensors in loamy sand soils (K. Sharma et al., 2021). For our study in loamy sand soil (S1) the TDR sensor performed better than VH400 sensors. Since they had lower RMSD value and higher R^2 values as compared to that of VH400 sensors (Table 3.9 and 3.10).

An improvement in sensor accuracy from Y1 to Y2 is evident with a decrease in RMSD value from 0.018 to 0.015 $m^3\ m^{-3}$ and an increase in R^2 from 0.56 to 0.87 (Table 3.10). Since all four sensors (2 reps at 0.3 and 0.6 meters soil depth) were installed on the same study plot a change in sensor location in the next year of the study (Y2) might have enhanced the correlation between neutron probe and Acclima TDR measured volumetric water content. Also, the calibration parameters slope and intercept were not significantly different from unity and zero, respectively, for Y1 and Y2 individually except for pooled data where intercept is significantly different from zero ($p<0.05$) (Table 3.10).

3.4.7 Comparison between watermark 200SS, Vegetronix VH400 and Acclima TDR sensors

Sensor (standard – neutron probe)	RMSD (m^3 m^{-3})	R^2
Watermark 200 SS	0.01	0.90
Acclima TDR 315 L	0.02	0.75
Vegetronix VH400	0.04	0.18

Table 3.11. Performance indicators – root mean square difference (RMSD) and coefficient of determination (R^2) between $\theta_{v\text{-}WM}$, $\theta_{v\text{-}TDR}$ and $\theta_{v\text{-}VH}$ in comparison with $\theta_{v\text{-}NP}$

In comparison with neutron probe ($\theta_{v\text{-}NP}$), watermark sensor ($\theta_{v\text{-}WM}$) resulted in lowest RMSD value (0.01 m^3 m^{-3}) followed by ($\theta_{v\text{-}TDR}$) TDR sensors (0.02 m^3 m^{-3}) (Table 3.11). Also, highest correlation with $\theta_{v\text{-}NP}$ was obtained for $\theta_{v\text{-}WM}$ with R^2 = 0.90 as compared to 0.75 for $\theta_{v\text{-}TDR}$ (Table 3.11).

Although, seemingly watermark sensor performed better than TDR sensors, it is important to consider that in the case of watermark sensors site-specific SWRCs (for each depth) were used to obtain $\theta_{v\text{-}WM}$ values and this was not the case with other sensors where general equations were used to estimate volumetric water content for all site depths. Hence, better performance accuracy of the watermark sensor may be attributed to site-specific and depth-specific calibration of the sensor through SWRCs and not the sensor itself. Also, the number of sensors deployed and total soil moisture datapoints analyzed for comparison varied substantially for different sensors, which may have impacted the results.

Overall, the results of the study confirmed that a fair response to changes in volumetric water content was observed for all three sensors since all sensors had RMSD <0.05 $m^3 m^{-3}$ when compared with neutron probe volumetric water content (Fares et al., 2011). Although many other factors can be considered for choice of appropriate sensors including cost, convenience, telemetry or data logging options in addition to accuracy of sensors. These additional factors are elaborated in previous studies to aid in choice of sensors (Kukal et al., 2020).

3.5 Conclusions

Site-specific soil water retention curves (SWRCs) for watermark sensors were obtained for two sites in central Minnesota using measured watermark soil matric potential data and measured neutron probe volumetric water content data. Good correlation between soil matric potential obtained from watermark sensor and volumetric water content measured by neutron probe at both sites and all three depths (0.3, 0.6 and 0.9 m) was suggested by high R^2 values. These SWRCs were also compared with general SWRCs estimated based on soil textural class. It was observed that SWRCs estimated based on general textural class at one of the sites performed better than those at the other site and this difference was likely the result of irregular pore geometry and greater variation in soil texture at the other site.

Site-specific SWRCs developed from measured $\theta_{V\text{-}NP}$ and $\Psi_{m\text{-}WM}$ data consistently performed better than general SWRCs based on soil textural class at both sites. Others have observed similar results. Therefore, site-specific SWRCs are recommended for the purpose of irrigation management. In this study, Irrigation Trigger Points (ITPs) developed based on measured data are calculated for two coarse-textured soils S1 and S2 that can aid in irrigation decision-making using watermark sensors. The suggested range for ITP at 35% depletion of available water holding capacity were 30-31 KPa and 29-30 KPa for S1 and S2 respectively.

The performance accuracy of three soil moisture sensors – watermark sensors, Vegetronix VH400 sensors and Acclima TDR sensors was evaluated in comparison to neutron probe based on RMSD and R^2 for coarse textured soils.

Overall, the results of the study suggest that Watermark sensors and Acclima TDR sensors performed better than Vegetronix sensors. As far as R^2 and RMSD values are concerned, watermark sensors performed best followed by Acclima TDR sensors. However better performance of watermark sensors may be attributed to site and depth specific calibration. The Vegetronix VH400 sensors exhibited poor sensor accuracy in estimating VWC.

Final conclusions

Nitrate pollution from agricultural activities can contaminate ground and surface water. Various farm management approaches including cover crops, nitrogen management and irrigation management have been found helpful in reducing nitrate pollution in prior studies. This study focused on irrigation management and demonstrated that significant reduction in nitrate leaching can be obtained through altering irrigation scheduling methods (amount and timing of irrigation) without significantly affecting corn yield in coarse textured soils. One of the irrigation scheduling methods – IMA, significantly reduced nitrate leaching as compared to other methods for all site years of the study. Although crop evapotranspiration was significantly reduced for this method, crop N uptake and corn grain yield were not significantly impacted in the study. The lack of difference in corn grain yield and N uptake between the different irrigation treatments indicates that there was enough irrigation to maintain the ETc required for crop production.

This study also suggested a positive relationship between percentage water use (PWU) and N uptake or N use efficiency. Three out of four site years of the study showed increase in N uptake with increase in PWU. Maximum PWU was observed for EPIC method of irrigation scheduling in the first year of the study Y1 and for IMA based irrigation scheduling in Y2 at both sites. Both IMA and EPIC methods resulted in significantly higher PWU on average in the study. PWU values were lower for CB and SM method of irrigation scheduling as they recommended higher irrigation amounts. In general, treatments with lower irrigation rates exhibited the highest PWU and vice-versa in all seasons and sites. Since both EPIC and IMA method resulted in better hydrological performance and are recent as compared to SM and CB methods some future work may be conducted in further investigating the impact of EPIC model and IMA tool based irrigation scheduling on crop production and nitrate leaching for better understanding their potential application in coarse textures soils.

The study also demonstrated that nitrate leaching is influenced by both amount and timing of irrigation. Both SM and CB method resulted in higher irrigation amounts, however due to difference in timing of irrigation maximum nitrate loss was observed in the CB method. Similarly, higher irrigation amounts not always resulted in maximum yield. The EPIC method based irrigation scheduling resulted in the highest crop yield for Y1 at both sites. However, this method called for more frequent irrigation with smaller amounts, which resulted in overall less total irrigation. Although no significant difference in corn yield was observed among irrigation scheduling treatments for all site years of the study.

In this study site-specific SWRCs were developed for watermark sensors using neutron probe which performed better than general SWRCs developed based on soil texture. Also, Irrigation Trigger Points for two coarse textured soils – Hubbard-Mosford complex and Arvilla sandy loam) were obtained in this study. To the best of author’s knowledge this is the first study to calculate ITPs for these soils and would aid growers in irrigation management through watermark sensors. Watermark sensors were also compared with two other sensors – Vegetronix

VH400 and Acclima TDR sensors. Since watermark sensors volumetric water contents were calibrated using site-specific SWRCs they performed better in predicting volumetric water content accuracy as compared to other sensors.

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